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THE DEVELOPMENT OF A PREDICTIVE PROBABILITY MODEL FOR EFFECTIVE CONTINUOUS LEARNING AND IMPROVEMENT

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THE DEVELOPMENT OF A PREDICTIVE PROBABILITY MODEL FOR EFFECTIVE CONTINUOUS LEARNING AND IMPROVEMENT

DISSERTATION

A dissertation submitted in Partial Fulfillment of the
Requirements for the degree of Doctor of Philosophy in the
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By

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ABSTRACT OF DISSERTATION

THE DEVELOPMENT OF A PREDICTIVE PROBABILITY MODEL FOR EFFECTIVE CONTINUOUS LEARNING AND IMPROVEMENT

It is important for organizations to understand the factors responsible for establishing sustainable continuous improvement (CI) capabilities. This study uses learning curves as the basis to examine learning obtained by team members doing work with and without the application of fundamental aspects of the Toyota Production System. The results are used to develop an effective model to guide organizational activities towards achieving the ability to continuous improve in a sustainable fashion.

This research examines the effect of standardization and waste elimination activities supported by systematic problem solving on team member learning at the work interface and system performance. The results indicate the application of Standard Work principles and elimination of formally defined waste using the systematic 8-step problem solving process positively impacts team member learning and performance, providing the foundation for continuous improvement Compared to their untreated counterparts, treated teams exhibited increased, more uniformly distributed, and more sustained learning rates as well as improved productivity as defined by decreased total throughput time and wait time. This was accompanied by reduced defect rates and a significant decrease in mental and physical team member burden.

A major outcome of this research has been the creation of a predictive probability model to guide sustainable CI development using a simplified assessment tool aimed at identifying essential organizational states required to support sustainable CI development.

KEYWORDS: Continuous Improvement, Team Member Learning, Learning Curve, Systematic Problem Solving, Toyota Production System

M. Abbot Maginnis

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THE DEVELOPMENT OF A PREDICTIVE PROBABILITY MODEL FOR EFFECTIVE CONTINUOUS LEARNING AND IMPROVEMENT

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I dedicate this dissertation to my family, especially my loving and patient wife.

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First and foremost I must acknowledge the consistent support of my wife and children. My wife Denise, has not only stood by me, but has cheerfully taken on the extra burden of continuing our household while I have been absent most weekdays pursuing both my education and work in another city for the past 7 years.

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Finally, it is only by the grace of God that I am where I am today, "Te Deum laudamus" (*We praise thee, Oh God).*

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CHAPTER 1: INTRODUCTION

The explicit research work performed in this study is intended to experimentally investigate the impact on learning of: 1) systematic problem solving to achieve Standardization, and 2) waste elimination using systematic problem solving at the team member (TM) / work interface. This was be accomplished by directly determining learning curves from teams of college students functioning as operators and a team leader /observer in small two-station assembly/disassembly cells. The variables investigated in this study are systematic problem solving (P/S) coupled with Standardization and waste elimination activities. The outcome of this research contributes to further understanding critical factors needed to develop sustainable continuous improvement (CI) or true lean environments within manufacturing organizations. The study accomplishes this by highlighting opportunity costs in terms of lost productivity and learning associated with generally unstructured methods commonly used to conduct CI activities.

The results of this investigation are intended to determine whether or not systematic P/S activities enhance TM learning compared to baseline results obtained from generally non-systematic improvement methods commonly performed as independent TM improvement activities. Depending on the outcome, these results will contribute to the creation of a predictive probability model for estimating an organization's progress towards creating a sustainable CI environment by assessing the degree to which the organization currently supports the fundamental aspects of systematic problem solving in support of standardization and waste elimination activities examined in this study.

Traditionally the role of engineering has been focused primarily on equipment and material needs. However, as a result of global pressures to increase quality and productivity and reduce costs in nearly all industrial sectors, especially manufacturing, the human side of the system has become more and more important (Fenner and Jeffrey, 2011).

Human involvement in any production system provides the potential to learn to learn and continuously improve. The ability to learn represents one of the most critical competitive advantages organizations can obtain (Moingeon and Edmondson, 1996) and developing this capacity has become synonymous with continuous improvement (Garvin, 1993) and Lean (Liker, 2004). Unfortunately, while there is no definitive, single source, estimates of the failure rate for companies trying to create sustainable and effective CI environments, often taking the form of a lean implementation, vary from 70% to 98% (Graban, 2005). This study is intended to improve theses outcomes by contributing to the understanding of the basic failure mode(s) associated with them.

The roots of continuous improvement (CI) go back to the teachings of Deming, Juran and Crosby (Sousa and Voss, 2002; Deming, 1986). The concepts behind CI are based on based on what Walter Shewhart called the *dynamic scientific process of acquiring knowledge* (Shewhart, 1939; Hall, 2006) which Deming introduced into Japan starting in the 1950s. Over time Deming modified Shewhart's 3-step inquiry learning model from Inspection-Specification-Production into the PDCA (Plan-Do-Check-Act) or Deming Cycle (Deming 1950; Hall, 2006). The PDCA cycle is the framework over which Toyota's *Kaizen* approach to continuous improvement exist (Imai, 1986; Ohno, 1988; TBP, 2005). By examining the primary components of "Kaizen" as Toyota practices it, this study intends to provide a more complete understanding of the basic CI requirements and demonstrate their value towards providing important learning and performance improvement where basic value is created, at the TM/work interface.

1.1. Problem Background and Uniqueness of this Work

The PDCA cycle is well known as the basis for problem solving and Kaizen or continuous improvement (Deming, 1994; TBP, 2005). However investigations into the basic drivers of continuous improvement appear to take the role of problem solving for granted in CI initiatives (MacDuffie, 1997; Spear and Bowman, 1999). In addition, problem solving to achieve and maintain standardization (also part of the Japanese concept of Kaizen (Imai, 1986; Ohno, 1988) is also often ignored (Berger, 1997). Practitioners responsible for implementing continuous improvement functions within organizations have followed suit, often ignoring both the role of systematic problem solving (Garvin, 1993; Spears and Bowman, 1999), and the initial requirement of standardization (Imai, 1986; Berger, 1997; Kreafle, 2007) in creating successful continuous improvement environments. Instead they appear to focus on implementing quality and productivity improvement tools such as 5S, visual management and other Industrial Engineering related tools as a primary component of their CI initiatives using a series of projects or activities which they call "Kaizen" or rapid improvement events (Womack, 2007). Ironically, those same tools, which are often seen as the foundation of TPS, were initially developed as part of the need to stabilize and standardize the work being done in response to systematic problem solving activities.

In a review of contemporary lean thinking, lean was defined as pertaining to both strategic and operational perspectives (Hines, et al; 2004). At the operational level, lean incorporates nearly all the various improvement initiatives illustrated in Figure 1.1.

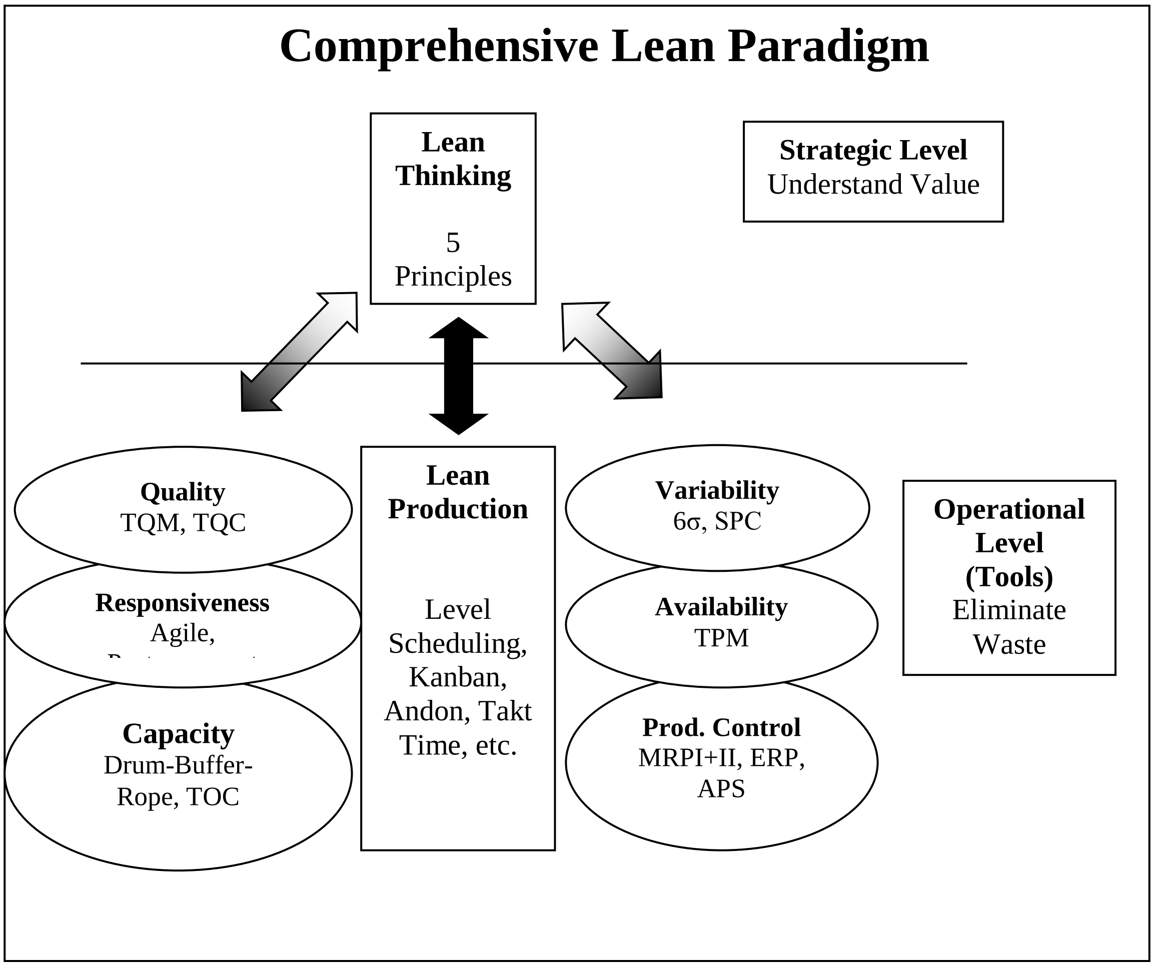

Figure 1.1. Lean paradigm showing quality and CI initiatives as part of Lean (Hines et al; 2004).

Besides improvement tools, Figure 1.1 illustrates the commonly accepted application of the so-called five principles of lean thinking (Womack and Jones, 1996) as providing the basis for understanding and strategically implementing lean. The five principles can be summarized as:

1) identify value,

2) map the value stream,

3) create flow,

4) establish pull, and

5) seek perfection (Lean Enterprise Institute , 2009).

Notably absent is any mention of Standardization or systematic problem solving in the figure or in the principles.

Although it can be argued problem solving and standardization are central features of the Lean paradigm, the omission of both problem solving and standardization in Figure 1.1 illustrates a basic misunderstanding of priorities in the thinking behind lean as practiced by Toyota. In all fairness, while the central role of Kaizen is often highlighted by Toyota, the critical nature of standardization and the deliberateness of systematic problem solving are often only implied. Many studies focus on the results of improvement activities such as rapid Kaizen events or the implementation of 5S, visual management or single minute exchange of dies (SMEDS), etc., often neglecting the importance of standard work (STW) and assuming effective systematic problem solving has and will always take place. As a result, the importance of systematic P/S and Standardization to create a sustainable lean system capable of CI appears to be undervalued and therefore often not vigorously sought after.

Two recent studies further illustrate how far removed systematic P/S and standardization are in current lean practice and thinking. The first is an investigation to examine contextual factors which may inhibit the implementation of lean systems (Shah & Ward, 2003). The study examines 22 manufacturing practices identified as "*key facets* *of lean production systems*" collected from 16 different references. Although two of the lean practices listed are "continuous improvement programs" and "quality management programs", there is no specific mention of either P/S or standardization. Another investigation to understand the role of specific lean work practices in creating a high-commitment lean culture lists 16 independent variables (Angelis et al; 2010), only one, "Improvement projects", remotely refers to P/S, and standardization is again not mentioned.

Considering the situation outlined above, it may not be surprising the success rate of continuous improvement initiatives over the last 30 years is mixed, fueling a growing debate over whether to attribute the failure rate to poor management practices or programmatic system related flaws (Hino, 2007; Rea, 2007). It is also not unexpected that given the inaccurate understanding of both the nature and intent of the concept of CI, there is no agreed upon definition of CI, giving rise to a number of popular management directed "improvement" programs in existence today, all based on some aspect of continuous improvement (Newton, 2009). Some of the more popular management programs studied in the continuous improvement literature include; total quality management (TQM) (Garvin, 1993; MacDuffie, 1997; Mukherjee et al; 1998; Lapre et al; 2000; Lapre and Van Wassenhove, 2001), management by objective (MBO) (Rodgers and Hunter, 1991), Just-in-Time (JIT) (Wantuck, 1989; Linderman et al; 2003), Six-Sigma (Choo et al; 2007; Anand et al; 2007) and lean systems engineering (Womack et al; 1991; Hayes and Pisano, 1994; Liker, 2004).

From the TPS perspective, there are three basic principles of Kaizen or CI (Imai, 1986);

1) Kaizen is process oriented, -- i.e., Before results can be improved, processes must be improved, as opposed to result-orientation where outcomes are all that counts.

2) Lasting improvements can only be achieved if innovations are combined with an ongoing effort to maintain and improve standard performance levels -- Kaizen focuses on small improvements to work standards which directly supports Taiichi Ohno's basic principle of "No Standard, no Kaizen" (Ohno, 1988).

3) Kaizen is based on the belief in people's inherent desire for quality and worth, and management has to believe that it is going to "pay" in the long run -- This supports the idea that improvements can't be driven from the top but must be part of collaborative efforts from top management to workers at the shop floor.

It is critical to understand the distinction between workers on the line having improvements done "to" them, "with" them, or "by" them. At best most so-called improvement activities are done "with" the front line, not "by' them (Kreafle, 2007).

Besides misunderstanding the original intent of CI activities, there is a problem in defining what is meant by "problem solving" from the TPS perspective. The difference primarily concerns the rigor associated with the activity since many companies now teach some version of problem solving based on PDCA and Toyota's systematic problem solving method. Examples include Ford's 8D method and the six-sigma DMAIC process. At issue are differences in application of the problem solving method. This difference has been illustrated in the literature using a healthcare example (Tucker et al;2002). The study focuses on P/S outcomes and distinguishes between first and second-order solutions. First-order solutions allow work to continue without trying to prevent the problem from returning. Second-order solutions are characterized by attempts to investigate and eliminate the underlying cause(s) of problems (Tucker et al; 2002). The core issue concerns the difference in outcomes based on the pursuit of either first-order (short-term) or second-order (long-terms) solutions and their effects on individual and organizational learning. Although limited research has been conducted on this issue, the results indicate the response of individuals to problem solving activities such as focusing on either first or second order solutions varies significantly. Tucker et al.,(2002) uncovered evidence that problem solving solutions intended to keep the system running but not to prevent their reoccurrence (first –order solutions) tended to stifle individual and organizational learning of front line workers. The results highlight the need to further understand the effects of problem solving activities at the team member/work interface, especially with respect to efforts to develop continuous improvement processes. To appreciate how the proposed study relates to the above situation requires some understanding of the systematic problem solving referred to in the healthcare study and the proposed research. The systematic 8-step P/S method used in this study is the came method used throughout all of Toyota Motor Corp. and is presented along with a summary of the basic elements of each step in Appendix EE. While the problem addressed in this research is not entirely new, the outcomes observed in previous investigations indicate a new research approach may be beneficial.

A simplified illustration comparing the situation resulting from the two problem solving approaches outlined above is presented in Figure 1.2. The resulting differences between the two approaches are illustrated by the space between CI and STW blocks for 2 “events”.

In Figure 1.2, the initial work being performed is described using an SOP (Standard Operating Procedure) which typically does not define specific task sequences, required material or cycle time requirements. Depending on the improvement method followed, abnormal tasks may or may not be eliminated and STW defined. However, if STW is not created and followed, improvements are often made as work-a-rounds or short-term solutions to problems as they are discovered and new SOPs are defined. IN this scenario, problem solving efforts are often informal, although both informal and formal P/S activities concentrate on finding solutions which allow the processes or system to continue. As a result P/S often results in finding and implementing short-term solutions (1st order P/S). Alternately, STW consists of specific task sequences, material requirements and cycle times. Work performed not directly defined by STW is considered abnormal and eliminated using systematic problem solving which has the specific intent of keeping the abnormality for returning. Work instructions which do not specify task sequence, material or cycle time requirements often result in the operators performing both normal and abnormal work as part of their SOPs. As a result, most problems (abnormal or non-STW is by definition a problem in systematic problem solving) are not eliminated but are either tolerated or resolved using worked arounds.

While learning in the form of performance improvement may occur using first-order solutions, it may be less than that expected using second-order solutions simply because the requirement to prevent reoccurrence of the problem often demands a deeper understanding of the processes and system. Additionally, greater variation in cycle time or performance time could also result (Deming, 1994) as well as reduced opportunity for team members to improve/learn (Tucker et al; 2002). The hypothesized results as either method is repeated, are seen in the next "event" on the graph

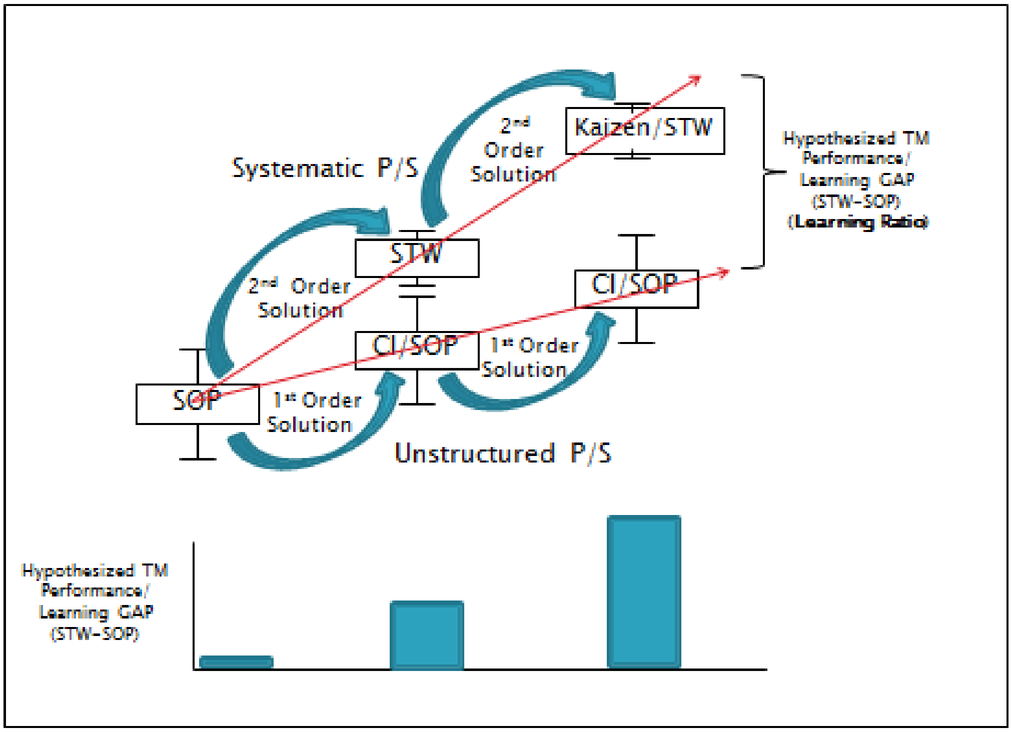

Figure 1.2. Conceptual illustration of part of the problem addressed in the proposed dissertation.

If organizations understand the fundamental factors enabling the success of TPS in supporting CI activities as a foundation of learning organizations, they are more likely to be successful themselves. The study presented in this dissertation represents a unique approach to more clearly understand the basic factors responsible for effective continuous improvement activities. The motivation behind this proposed research is to more fully understand the role of systematic problem solving and standardization, followed by "Kaizen" (in the form of waste elimination in this study) in creating sustainable continuous improvement processes. This study attempts to investigate the amount of improvement and learning occurring (if any) when the focus is primarily using systematic P/S to achieve stable and standard conditions before making other improvements by eliminating waste. This is the basic method practiced by Toyota (Ohno, 1988, Imai, 1986, Kreafle, 2007). In this study the above conditions are contrasted with conditions allowing team members to improve on their own in an unstructured, non-systematic manner.

1.2. Research Objectives

The proposed research will contribute to the basic understanding of underlying factors responsible for creating sustainable continuous improvement (CI) processes by investigating the effects of an applied continuous improvement model on productivity/learning at the team member/work interface under experimental conditions. The laboratory-based experiments use Learning Curve Analysis (LCA) and quantitative analysis techniques to show the effects of; (1) systematic problem solving to support standardization and waste elimination, (2) the impact of 1st and 2nd order P/S methodologies on team member and team productivity and learning in conjunction with team member mental and physical burden are affected. The results will be used as the basis for developing a predictive model and assessment tool for analyzing sustainable CI development.

The learning curve (LC) analysis is based on individual cycle times and was selected as the basis of the analysis because measuring quality (i. e., defects) or other productivity metrics which often aggregate the experiences of individual team members dong the work. In addition, using higher level results such as defect rates or the number of “successful” improvement activities conducted provides too course a measure of learning within the time frame of the study. Cycle time based LC analysis combined with qualitative analysis of team member attitude and burden has several advantages over empirical field studies. First, the construction of learning curves (LCs) based on real-time quantitative data from individual team members provides direct evidence of the effect of the independent variables on productivity and learning rate. Second, quantitative data collected from self-assessments are collected at 16 unit cycles, giving real-time feedback on impact of treatment on individual treated and untreated team members. Third, there are no other organizational elements which can adversely influence the results, and finally, the results can be used to create a rigorous model based on fundamental team member responses to the application of the treatment and inform future CI implementation programs.

The following null hypotheses will be investigated;

1. H_1: Initiating the use of standard work along with 8-step problem solving thinking (P/S + STW) to eliminate obstacles to performing normal work does not significantly affect individual team member learning as opposed to allowing team members to perform both normal and abnormal work.

2. H_2: Introducing the formal concept of the seven-wastes and facilitating 8-step problem solving (P/S + WE) to eliminate them does not significantly affect individual team member learning as opposed to relying on individual notions of waste and improvement opportunities.

3. H_3: System productivity is not affected by the application of systematic problem solving to support standardization and waste elimination activities used in this study.

Examining the above hypotheses will demonstrate the effects of both independent variables (P/S + SWT and P/S + WE) on team member learning and help provide a clear pathway for organizations wishing to develop systems capable of sustaining continuous improvement activities. The methodology used here is based on a standardization-problem solving–waste elimination-problem solving (STW + P/S + WE + P/S) improvement process implicitly embedded within the Toyota Production System (TPS). This methodology appears to represent the underlying thinking responsible for the development of the so-called "lean tools" such as 5S, Standard work, andons, kanban, and visual management which mistakenly became the primary focus of many CI initiatives in industry (Garvin, 1993; Spears and Bowman, 1999; Womack, 2007). The same standardization-problem solving–waste elimination-problem solving improvement process is still being conducted throughout Toyota at every level. The primary treatment in this study is the application of a systematic problem solving process conducted in response to challenges to performing STW and eliminating waste, which is roughly equivalent to so-called "Kaizen" activities on the shop floor.

CHAPTER 2: LITERATURE REVIEW

2.1. Background of Learning Curve Research

The earliest studies on human learning were initiated by experimental psychologists at the end of the 19^{th} century. In 1899 an article was published in the *Psychological Review* on the application of telegraph operators' skills. In 1913 Hermann Ebbinghaus, a German researcher published a book on memory which included personal experiments on individual learning. F. W. Taylor (1911) also considered the concept of learning very early on in his research. In his work on scientific management Taylor discussed the need to make cycle time allowances for workers learning new tasks. In 1936 Wright (Wright, 1936) published the first learning model using data from the aircraft industry. His model has become known as the Learning Curve. Simply stated Wright's expression for the learning curve says the completion time for an airplane decreased by approximately 20% each time the number of aircraft made doubled. Over time, this has become the most familiar form of the learning curve and has been applied to both individual and group or organizational learning outcomes. In general, the learning curve states that for repetitive processes, the amount of time required to perform a task will decrease by approximately 20% as the number of times it is repeated doubles. Wrights learning curve is also called the "Power Curve", "Power Model", or "Power Law", and is the most commonly used learning model by industrial engineers. Although the rate of learning may vary, the Power Law form of the learning curve has been used to describe both individual and group learning rates occurring in a wide variety of industries from airplanes to automobiles to ships to electronics.

Despite the fact Wright's model is essentially an organizational model and was developed for very large products with long cycle times using aggregated data, it has also been used by a number of researches to study individual learning (Conway and Schultz, 1959; Baloff, 1966 & 1971). Often individual studies focus on skill acquisition and are performed by behavioral scientist based in large part on laboratory experiments (Van Cott and Kinkade, 1972; Anzai and Simon, 1979; and Mazur and Hastie, 1978). These experiments are generally designed to measure responses to a variety of stimuli. In most cases there is an element of decision making involved ranging from the simplest case of responding to a single light to those involving very complex tasks such as training pilots.

From an applications perspective, learning curve (LC) models are often used to predict performance of ongoing operations (Globerson, 1980). They are helpful with planning and control by estimating future performance and therefore assist in determining future resource requirements. However, some studies suggest estimated future performance depends heavily on both individual and group motivation (Gershoni, 1971). Many individual studies are designed to study autonomous or psychomotor learning only (direct learning based on repetitive motions, ie "practice makes perfect" learning). According to Globerson (1980), LC models can be divided into 2 major groups: 1) individual, 2) organizational. For individual models the focus is on personal performance improvement through repetitions. Most results indicate learning is dependent on the ability of the worker to work faster (increase the speed of their motions), to reduce motions or perform two motions simultaneously. Organizational LC models are used to describe the performance improvement of large groups, also through repetition. Wright's model is organizational since it describes the performance of a group of people as they make airplanes. In organizational models, results can't be attributed to a single individual. However, the improvement of the organization is influenced by individual performance as well as the following variables; a) aggregation of individual learning curves, b) extent which management techniques (method improvement, work scheduling, inventory control, incentive systems) are implemented. c) the extent to which management can plan, implement and control organizational activities, and d) the extent which management can record individual information and knowledge through proper documentation so it becomes part of organizational knowledge.

The vast majority of organizational learning curve research has depended on the use of aggregated data, ie proxy data, pertaining to cost, quality or productivity applied to time frames during which the researchers had generally little or no control over the production environment studied (Adler, 1991). Such studies have several inherent weaknesses. First, the data is usually historic in nature and is therefore only weakly tied to specific knowledge and events occurring at the work/team member interface where the actual value is created. Secondly, the nature of the aggregated data makes it difficult or impossible to identify the exact activity creating the learning effect observed. Some studies focus on predicting the ultimate productivity or process yields possible by creating so-called "yield models", designed to optimize equipment utilization to drive improvements, without regard to individual team member learning (Dance and Jarvis, 1992; Dar –El, 2000).

In systems engineering and operations management much of the research involves understanding factors affecting the learning curve. At the actual performance level within organizations, it has been found the shape and basic elements of the learning curve such as the learning index *Φ* and learning rate or learning constant *b* have been found to vary both within and between organizations, even when they produce the same or similar items (Argote, 1999). In most of these studies the learning constant or rate is considered a constant derived from the total learning curve which includes a cognitive and autonomous or psychomotor component. However, Dutton and Thomas (1984) advocated treating the learning rate as a dependent variable and not a constant which lead other researchers to consider whether the learning rate could be changed. Following this line of thought, a study by Jaikumar and Bohn 1992 concluded factory personnel should deliberately try to enhance improvement rates (Lapre, 2000). Also, based on a case study looking at waste elimination over a 10y year period, Lapre et al., (2000) found only projects in which involved operators knew specifically both the how and why the particular waste occurred were able to significantly reduce it. Other projects in which one or the other of these elements was missing were found to have no impact on waste elimination.

Over time several hypotheses have been put forward to describe how industrial workers learn. Among them is a study by Crossman (1959) which concluded unskilled workers learn new tasks through a series of trial and error cycles in which workers try out various methods, rejecting less successful ones and focusing increasingly on the ones providing the greatest success. Crossman also suggests that expert ability pertains more to knowing which method to use at a given time as opposed to having the best coordination or motor skills. Dar-el (2000) cites a study by Caspari (1972) involving a Methods-Time-Measurement (MTM) analysis of a task at different stages. In it, he found most workers tend to increasingly deviate from the proscribed MTM movements as they become more experienced with the job. Gershoni (1979) found workers were often able to perform to MTM standards after very little training and that most progress seen (i.e., learning) was the result of developing improved task performance patterns rather than working with more dexterity, thus supporting Crossman's original observation that experienced workers tend to follow more efficient methods rather than be able to work faster or possess more agility than their peers. A study by Dudley (1968) showed worker performance times were symmetrically distributed over the range of demonstrated cycle times, and that over time, while the results remained within the original performance range, they became skewed at the lower side of the distribution curve, indicting no new knowledge was obtained, rather only increased operator skill at performing the task.

More recent studies designed to measure induced or cognitive learning are based on the result of continuous improvement activities. However, most of them suffer from the same weakness outlined above along with an inherent bias arising from the definition of induced learning itself as being the result of conscious *management* actions (Li and Rajagopalan, 1998). The implication is there is little significant cognitive learning occurring where the work is being performed without direct management involvement (i.e., management directed projects). However, the success of the Toyota Production System is in its ability to harness the cognitive ability of team members doing standard work with the assistance of a team leader to handle abnormal conditions and to assist in collaborative problem solving activities (Hall, 2006). These activities are aimed at not only enabling workers to perform standard or normal work, but also at helping them identify and eliminate waste and abnormal occurrences through a structured problem solving methodology.

The research proposed here is designed to overcome some of the weaknesses mentioned above *and* to separate out management driven versus team member or group driven induced learning affects. This will be accomplished by focusing on the work conditions at the point of value creation represented by using a simplified set-up of the cylinder factory under controlled experimental conditions presented. This type of experimental design allows the use of first-hand data as each process is performed and immediately after each run.

2.2. Single and Double Loop Learning

One widely accepted definition of learning is articulated in terms of when it occurs, which according to Chris Argyris (1982), a leader in organizational learning research, is when errors are detected and corrected. According to this definition, learning does not occur as the result of detecting errors (defined as a mismatch between intention and actuality) or discovering new insights, but only if the errors are corrected or new insights or discoveries are acted upon. This makes learning an action-oriented activity, ultimately based upon the actions of individuals or groups. The type of learning which occurs depends on the scope of the corrective actions taken, and can be defined as either single loop or double loop learning. Single loop learning occurs when the mismatch is corrected without questioning underlying values or policies while double loop learning involves questioning or changing underlying values or policies followed by changes in work or actions (Argyris, 1982).

Single and double loop learning models were introduced as part of the field of System Dynamics by Jay Forrester (1961) and further developed by John Sterman and Peter Senge. System Dynamics describes organizational characteristics as part of a complex system and tries to understand how cognitive features of individuals interact with those characteristics in terms of stocks, flows and feedback loops (Radzicki and Taylor, 1997). Unfortunately, human cognition is relatively insensitive to feedback delays and nonlinearities (uneven, sporadic or disproportionate responses) which results in an inaccurate interpretation of feedback information (Sterman, 1989). These inaccuracies, which increase as the worker or team member, become further removed from the actual work and the feedback response to their work becomes less obvious. The result is the effect that corrective actions on problems are misinterpreted, which distorts process learning and leads to what Levitt and March called "superstitious learning", a condition where assumptions or vague inferences are treated as factual information (Levitt and March, 1988). A central axiom of System Dynamics is that the structure of the system determines the results in organizations but because much of the feedback coming from the system is nonlinear in nature, managers tend to perceive outcomes as the result of events, not structure. Since both Single and Double loop learning depend upon feedback loops to validate the correctness of the response, either one may result in misunderstanding or misinterpretation of the results, leading to the requirement for an awareness of what Senge calls *personal causal effects* to help create and sustain learning organizations (Senge, 1990).

From an individual perspective, the occurrence of single loop learning, where work may change without regard to underlying assumptions or conditions, builds in personal biases which tend to obscure fact-based causal relationships between actions and outcomes over time. This can lead to inaccurate mental models subconsciously created to support actions which can lead to the proliferation of errors and reinforce anti-learning personal dynamics (Argyris and Schoen, 1974; Argyris, 1982). This may also give rise to the development of what Argyris calls “skilled incompetence”, where members of the organization perform activities based upon inaccurate assumptions or “theories-in-use” about the work being performed (Argyris, 1993).

By way of analogy the experimental design created for this dissertation incorporates both single and double loop learning into the experiment. Single loop learning occurs when autonomous learning is prevalent as determined by the value of the learning constant. In this type of learning, operators can adjust their work to overcome problems by creating work-a-rounds without considering the underlying factors contributing to the problems encountered. Conditions for the occurrence of double loop learning are associated with specific treatments applied to selected teams in runs three and four. Double loop learning involves questioning the underlying factors responsible for current conditions and making changes based upon a clearer understanding of the situation surrounding the problem. Thus double loop learning is more representative of cognitive learning. As noted by Dar-El (2000), both types of learning contribute to the overall makeup of individual learning curves, but over time, most operators will exhibit autonomous learning almost exclusively as evidenced by the nearly horizontal component. However, one of the goals of this study is to demonstrate the occurrence of double loop or induced learning in experienced operators associated with systematic problem solving in support of standard work and waste elimination activities

Single loop learning is modeled using the baseline condition outlined in the experimental set-up because it primarily involves developing autonomous or mechanical skill and creating work-a-rounds to overcome problems encountered doing the work.

Double loop learning is more likely to occur as the results of the treatments given selected teams in runs 3 and 4 because it encourages team members to question and change pre-existing conditions pertaining to how the work is done. In the treated teams, operators are asked to follow standard work and use systematic problem solve to overcome challenges to performing it in run 3 and to identify waste and use the same systematic problem solving method to eliminate it in run 4. As previously mentioned, one hypothesis of this study is that 8-step problem solving training, coupled with the implementation of standard work requirements and waste elimination concepts re-introduce cognitive or double loop learning further down the learning curve than would normally occur. If true, such treatments would be expected to result in improved productivity as evidenced by a decrease in cycle time.

The problem addressed in this research deals with the need to increase organizational learning as a means to improve strategic capabilities and develop competitive advantage. This study examines learning at the individual level and focuses on measuring productivity increases at the worker/product interface. In particular, this research addresses the lack of direct empirical learning curve data at the individual or team member level by demonstrating the effectiveness of certain core TPS principles to enhance learning curve outcomes under experimental conditions outlined in this study..

2.3. The Learning Curve

The original learning curve model was first articulated in the 1930s as the result of a study of the airplane industry (Wright, 1936). Since then it has been found to be applicable to a wide range of industries. Learning curves have been used to study individual and organizational performance in a variety of settings (Carlson, 1987; Towill & Cherrington, 1994; and Gunawan, 2009).

The learning curve can be characterized by repetitive work by either groups of people or individuals and thus relates to either organizational or individual learning. There are many models but the most commonly applied learning curve model is presented in Figure 2.1 based on the following equation (Dar-el, 2000; Gunawan, 2009):

$$t_n = t_1 \; x \; n^{-b} \qquad (2.1)$$

where; n = the number of cycles or repetitions completed

t_n = the performance time to complete the n^{th} cycle

t_1 = the performance time to complete the first cycle

b = the learning constant

One of the important features of the learning curve is that each time the number of cycles doubles, the performance time decreases by a factor related to b, the learning constant. Traditionally, each learning curve is characterized by a unique learning rate b which is constant, and t_1 or similar parameter such as cost, defect count or cycle time. Another feature of the learning curve is that it visually represents two types of leaning, commonly described as either induced or cognitive learning, or autonomous or psychomotor learning.

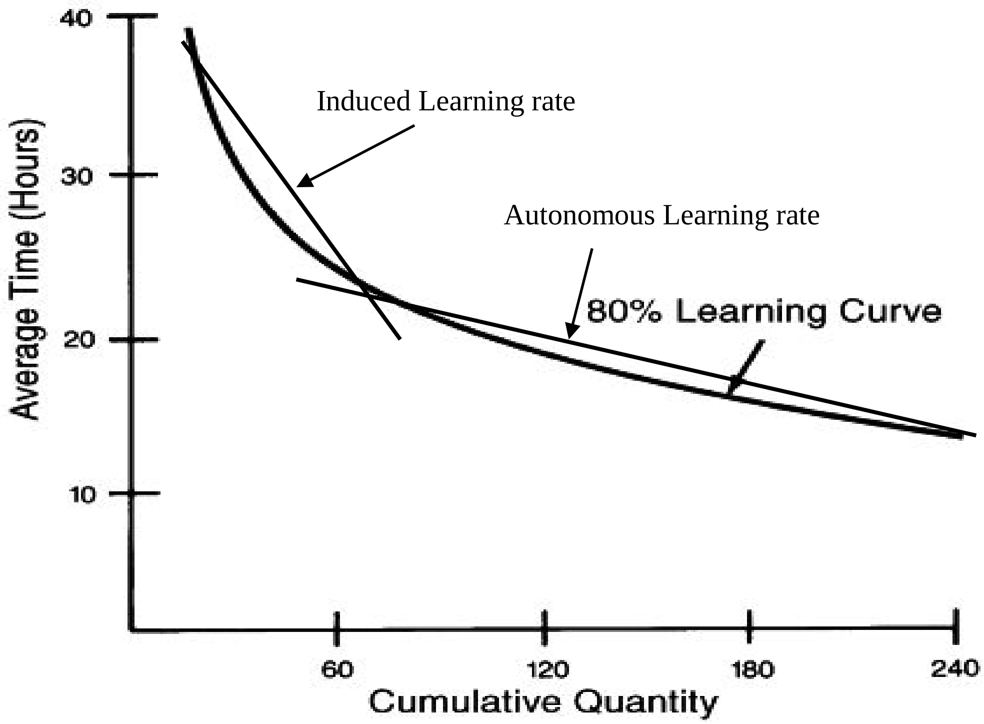

Figure 2.1. Illustration of a typical learning curve showing Induced and Autonomous learning regions.

Simply stated, cognitive or induced learning is dominant when performing complex tasks, acquiring new knowledge or skills, and where using long-term/short-term memories are needed to successfully complete tasks. Autonomous or psychomotor learning is commonly associated with the team member /work interface and is understood as being direct learning based on repetitive motions, i.e., "practice makes perfect" learning and is measured in terms of speed, precision, distance, procedures, or techniques in execution; activities most often associated with team members doing repetitive work (Bloom, 1956). It is generally agreed the initial shape of the curve is dominated by cognitive learning whereas the later, more level area is attributed to the occurrence of autonomous learning (Dar-El, 2000).

The majority of learning curve studies in the literature focus on group or organizational learning. Individual studies tend to be concerned with understanding how learning takes place rather than factors affecting it (Yelle, 1979).

Most learning curve models are based on large quantities of historic “proxy” data such as defect counts or project completion times. This type of data has been used determined important learning curve parameters such as the estimated initial time to completion t_1 and how the learning rate b varies from one company to another or at different locations within the same company, even when the same or comparable processes are being performed. One reason for this variation may be the work organization existing at the specific work locations studied. In general, while learning curves have been developed for a variety of work environments, they reflect the nature of the work more than the organization of it. According to Jaber and Sikstron (2004), studies by Argote (1993) revealed most learning curve studies captured individual, organizational and outside influences together. As a result, specific affects due to such things as work organization or adherence to standard work etc. are lost in the analysis. The general response of the organizational learning community appears to be towards focusing on the organization instead of the individual work within the organization. To my knowledge the effect of the individual work organization factors such as whether or not there is Standard work in place and in force has not been studied with respect to the learning curve parameters.

This study proposes a modification of the existing learning model which describes induced learning as the result of management directed improvement activities. In the experimental model explored here, the induced learning component is hypothesized to move to the team leader/team member level, where learning opportunities are strictly focused on the work being performed, instead of more broadly-based knowledge acquisition activities generally associated with management level induced learning. To evaluate this, the current study compares the effectiveness of a specific individual continuous improvement model utilizing the collaborative nature of the team member and team leader's roles to identify and make improvements. While it is widely acknowledged continuous improvement depends upon the operator's knowledge and is strongly influenced by the design of the overall system, there are few empirical studies designed to understand the impact of basic system elements such as the use of systematic P/S methodology to support STW and waste elimination on operator knowledge or awareness of improvement opportunities.

2.4. Convergence of Disciplines

From an engineering perspective the first challenge in manufacturing is to determine the most efficient way of constructing a system capable of meeting the customer's needs. Traditionally, the response of the engineering community has been to respond by determining equipment, material and manpower requirements capable of meeting customer demands at the quantities anticipated by the organization. The second engineering challenge is to help ensure the system is capable of sustaining itself in order to continuously meeting customer needs in the quantities required within prescribed quality and cost constraints. The last basic requirement is that the system be able to evolve to meet future demands and opportunities. Meeting those ongoing challenges require a robust culture of continuous improvement requiring the application of knowledge from three seemingly unrelated academic areas; organizational learning, industrial psychology and engineering. The basic foundation of this work lies with the conjunction of those disciplines into a field called systems engineering. Figure 2.2 illustrates this relationship and their focus on creating production systems capable of optimizing quality, cost and productivity. This research is the direct result of the need for organizations to better understand these relationships in order to gain a clearer, more fundamental understanding of the factors responsible for continuously improving the manufacturing environment which represents a vital area of research for healthcare, transactional, government, educational and manufacturing, especially with respect to long term competitiveness and sustainability.

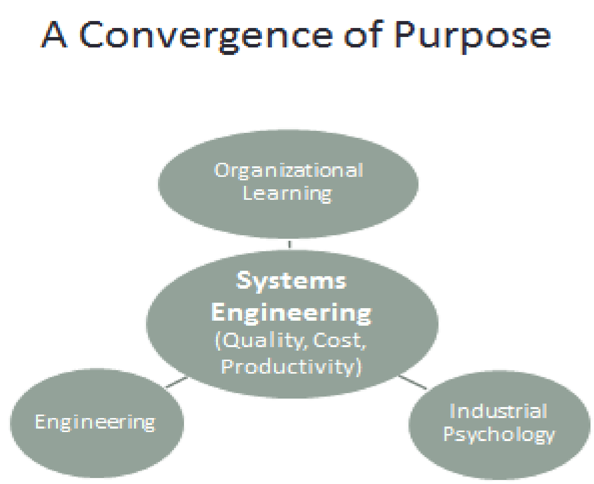

Figure 2.2 . The relationship of organizational learning, industrial psychology and systems engineering with respect to continuous improvement.

This research presupposes a systems perspective where all processes are connected by pathways in which materials and or information move from one process to another (Spear and Bowen, 1999). The goal of the system is to utilize each component (process or pathway) to create a product or perform a service that is valuable to a customer (i.e., is willing to pay for in some manner) (Deming, 1986). The first challenge from an engineering perspective is to determine the most efficient way of constructing the system to meet the customer's needs which have traditionally been addressed by determining equipment, material and manpower requirements capable of meeting customer demands at the quantities anticipated by the organization. The second engineering challenge is to help ensure the system is capable of continuously meeting customer needs in the quantities required within prescribed quality and cost constraints. Meeting those ongoing challenges require a robust culture of continuous improvement requiring the application of knowledge from all three areas identified in Figure 5, organizational learning, industrial psychology and engineering.

2.5. Engineering

The emergence of systems thinking and the increased realization of the importance of both technical and human support structures to sustain standardization and CI activities now require the application of engineering principles to human dimensions. The role of the engineering is shifting from the traditional silo-based engineering paradigm to a new, cross functional-based system engineering paradigm. One result of this shift is to blur the lines between equipment and materials-centric applications to include human dimensions as well. New disciplines such as human factor, ergonomic and organizational engineering as well as lean systems engineering are examples of this. Increasingly engineering professionals must consider issues such as stakeholder involvement, knowledge management and negotiating shared commitments on action (Fenner and Jeffrey, 2011; Savitz, 2006). The human dimension becomes even more critical for success as the scope of system requirements expand to encompass concepts such as the goal of meeting triple bottom line requirements or the 3Ps (Profit-People-Planet) and supporting important sustainability frameworks such as the 6Rs (Reuse, Reduce, Recycle, Remanufacturing, Redesign, and Recover, known as the 6Rs) (Jawahir et al; 2006). From a scientific perspective it is important to understand how and why people react the way they do, but from an engineering perspective, it is important to be able to use this knowledge to design systems which, along with the proper equipment and materials, has the best chance of meeting customer demand and are capable of meeting future demands as well.

2.4. Organizational Learning

Along with the emerging systems perspective for manufacturing there has been an increased focus on organizational development and learning (Senge, 1990; Garvin, 1993; Levine, 1995; Argote, 1999), from which has sprung a popular term called the *learning organization*. While various definitions of a learning organization have been developed, core concepts include the ability to continuously improve and awareness of the strategic importance of CI as a tool for developing a competitive advantage (Moingeon and Edmondson, 1996). CI is also defined in the context of organizational culture, commonly referring to Toyota's ability to sustain continuous improvement activities as the gold Standard of learning organizations (Liker and Hoseus, 2008).

It is not surprising that most studies associated with organizational learning and continuous improvements have focused on the management levels within organizations since cognitive or induced learning involves the acquisition of knowledge and the development of intellectual skills, activities most often associated with management (Bloom, 1956).

As previously mentioned, research on learning organizations and continuous improvement studies in particular have most often focused on management levels within subject organizations. Often these studies employ learning curves as a means of visualizing learning using results garnered from aggregated data such as defect rates, project completion time, and product costs etc. as independent input variables.   Such studies have several inherent weaknesses. First they measure outputs based upon vaguely defined and often uncontrolled continuous improvement processes applied over time frames in which the researchers generally had little or no control over the production environment studied (Adler, 1991). Second, most studies focus on management activities as the focal point of *induced or cognitive learning* occurring (Globerson, 1980; Dar-el, 2000). Third, most individual studies are designed to study autonomous or psychomotor learning.

The improvement of organizational performance is effected by the actions of its individual members. Besides individual performance, organizational learning curves are influenced by: (1) the aggregate of the individuals in the group: (2) the extent of management directed improvement activities implemented: (3) the extent of management control over activities: (4) the extent management captures the individual knowledge of the group (Globerson, 1980).   This line of thought appears to justify the prevalence of organizationally oriented learning and learning curve research which dominates the literature (Argote and Epple, 1990; Towill and Cherrington, 1994; Gunawan, 2009). With respect to continuous improvement and the implementation of lean practices, these studies often take the form of case studies designed to examine the effects of relatively high level changes introduced through *Kaizen* events or systematic changes on productivity or quality. Few if any studies focus on the individual learning experienced by team members at the work interface.

A basic understanding of most organizational development professional is organizational learning requires greater individual learning than just improved technical skills which is the most common contribution associated with individual team members (Watkins and Golembiewski, 1995). To them organizational learning involves continuous transformative learning events as opposed to single, isolated events, and transformative learning alters the assumptions about cause and effect (Kofman and Senge, 1993; Watkins and Marsick, 1993; Watkins and Golembiewski, 1995). The majority of individual team member learning in a production environment can be called *autonomous* due to its repetitive nature and because it involves improvement of psychomotor skills. In most production environment team member tasks on the shop floor tend to lack cognitive demands (think "leave your brain at the door") (Dutton and Thomas, 1984). However, from a TPS perspective, their work is the primary source of knowledge in the organization because they are the only members of the organization engaged in creating *value* to the customer. Without team member engagement in continuous improvement activities, critical process information may be missed. Therefore the cognitive involvement of team members is required. The critical component team members have is direct knowledge of process conditions. Depending on the structure of the system components such as the level of standardization and problem solving capacity, team members can immediately recognize and eliminate performance gaps and set new standards to prevent them from re-occurring. This basic feedback forms the foundation for understanding and learning in complex dynamic environments (Sterman, 1994). Disruptions in the feedback loop of cause and effect of work constitute a major barrier to organizational learning. Sterman listed several factors including; separation of cause and effect in time (not seeing a problem when it occurs), ambiguity of results (no standard to compare with), misperception of feedback, and finally poor inquiry and scientific skills. However, the need to a systematic problem solving methodology to eliminate the cause of disruptions was not specified.

2.6. Industrial Psychology

Industrial psychology includes human resource management (HRM) which has a significant impact on operations. Figure 2.3 introduces a model illustrating the relationship between HRM and operations management (OM) factors contributing to overall team member performance (Bordeau et al; 2003). In particular the model shows the interdependence of behavioral and contextual insights on the development of various aspects of an organization. Notice the interdependency between learning / development, and organizational structural aspects of the contextual framework, and overall operation performance from a behavioral perspective.

According to Bordeau et al; (2003) most individual work behavior models consist of the following three major elements:

1) TM capability: the skills, knowledge and abilities to execute some aspect of organizational objectives,

2) Opportunity: to provide situations where actions to help meet organizational objectives can be identified, and

3) Motivation: the drive to execute actions which are linked to the organizations objectives and rewards.

From these three elements two distinct models have developed over time. The first states team member performance is a primarily a function of ability and motivation (Vroom, 1964; Maier, 1955; Cummings and Schwab, 1973). The second model states the work environment determines the extent that motivation and ability affect performance (Gilbreth, 1909; Dachler and Mobley, 1973). More recent work suggests that situational constraints and opportunity are key to developing a more effective work performance theory (Campbell, 1999; Howard, 1995, Ilgen and Pulakos, 1999). The engineering aspect of these models is to understand how these factors affect the overall performance of the individual and the system.

Research on individual and group performance indicates that goal setting and feedback together accelerate learning more than in situations with feedback or goal-setting only or no goal-setting or feedback given at all (Locke and Latham, 1990; Kluger and DeNisi, 1996; Greve, 2003). These studies also show that although individual and groups will improve without specific goals or feedback, the rate or amount of improvement is generally be less than would otherwise be obtained. Goal setting-performance feedback theory can provide intrinsic motivation for improvement as illustrated in Figure 2.4. Unfortunately the ability of individuals to improve in spite of less than optimum circumstances can distort this relationship, leading to a flawed understanding of it depending on the clarity of work and other process-related information present. The result is activities designed to clearly define and Standardize work are often neglected or overlooked, especially at the team member/work interface.

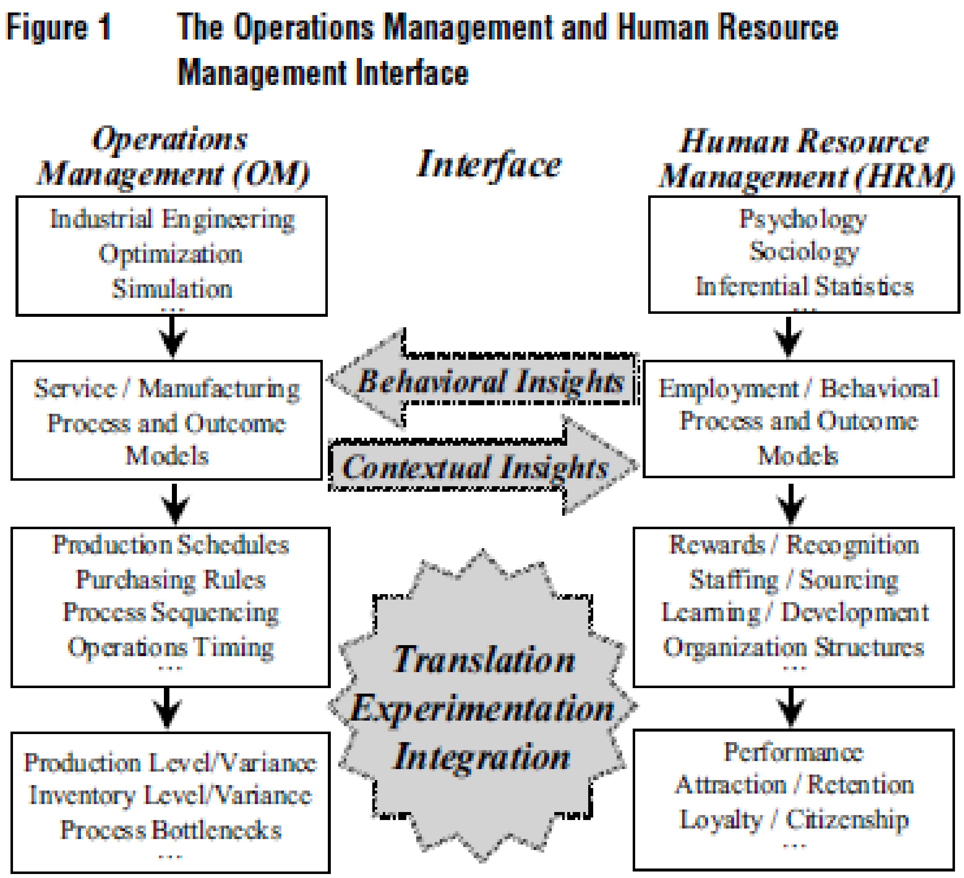

Figure 2.3. An operations management-human resource management interface framework illustrating the importance of learning and structure to operational performance (Bordeau et al; 2003).

Unfortunately, for many people introduced to Toyota and the Toyota Production System (TPS) in the context of "lean", Toyota's concept of work seems more specific and methods oriented than most workers in the west are used to. The idea of a worker performing "Standard work" is seen by many as restrictive and somehow insulting to expect workers to follow it so narrowly.

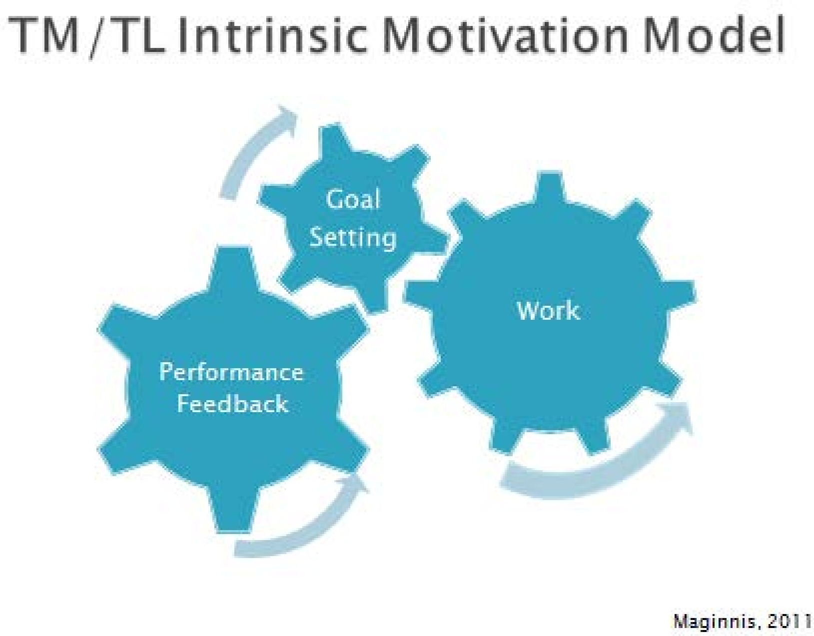

Figure 2.4. The relationship between individual and group work with goal setting and performance feedback as a means to provide intrinsic motivation for improvement.

2.7. Summary

The success of the Toyota Production System (TPS) is primarily based on the principles of standardization and continuous improvement (Ohno, 1988; Kreafle, 2007). An outcome of the successful implementation of the Toyota Production System (TPS), commonly called lean, is the development of a so-called the learning organization (Garvin, 1993) based on the principle of continuous improvement (Hall, 2006; Liker and Hoseus, 2008). The ability to sustain continuous improvement activities is considered an essential core competency for achieving and maintaining a competitive advantage in today's global economy (Womack et al; 1990; Moingeon and Edmondson, 1996,). Unfortunately the majority of companies attempting to create a sustainable continuous improvement culture fail (Graban, 2005; Womack, 2007; Liker & Hoseus, 2008).

In TPS the term *Kaizen* is used to describe improvement activities which are based on a standardized system and processes (Imai, 1986). Unfortunately, the translation of the concept of Kaizen into non-Toyota organizations focuses on "improvement", without explicitly stating the importance of the "standardization" component (Berger, 1997). The literature suggests most companies either overlook or undervalue the importance of standardization and the use of systematic problem solving ((Shah and Ward, 2003; Angelis et al; 2010). Instead they focus on well-intended improvements, often encompassing activities which results in what Deming calls "tampering" with the process or system (Deming, 1994). Tampering is a well-intended improvement activity conducted without a clear understanding of the cause of the variation being addressed and which ultimately leads to greater variation than before. The size and complexity of most organizations along with the "Hawthorne effect" often obscure the effects of tampering yet Deming estimated as many as 95% of management decisions for improvement actually result in loss of capability in some form or another. Ironically, many of the "continuous improvement" tools used in these activities were developed by Toyota as the result of systematic problem solving to achieve and maintain standard conditions (Kreafle, 2007). This highlights one of the basic questions investigated in this dissertation; what is the effect on team member learning using systematic problem solving to support standardization and waste elimination activities?

Learning in a manufacturing environment takes place through many mechanisms (Terwiesch and Bohn, 1998). Investigations into how problem solving and learning occurs in manufacturing generally neglect the action of team members doing the work, instead focusing on the activities of engineers and management (Lapre et al; 1996).

Studies examining factors effecting continuous improvement tend to look at activities and results at the group level and above. However, assuming individual learning is the ultimate foundation for continuous improvement, it is critical to look at factors and effects at the team member/work interface. One of the primary objectives of this research is to develop a continuous improvement model based upon a laboratory investigation of individual team member learning at the team member/work interface presented in Figure 2.5. This study is designed to illustrate the effectiveness of a specific continuous improvement process based upon a goal setting-performance feedback type model AND to measure the amount of relative improvement occurring under each condition studied. The figure illustrates the relationship between the Intrinsic Motivation Model based on goal setting-performance feedback theory presented in Figure 2.4 coupled with systematic problem solving. In this case systematic problem solving can be seen as the primary intervention strategy designed to increase team member motivation to address problems with meeting the standard (out of standard condition) or a new continuous improvement target (improvement or Kaizen condition) (Kluger and DeNisi, 1996).

The outcome of this investigation will add to current understanding of the effect of standardization and systematic problem solving on individual team member learning and lay the groundwork to formally include standardization as a legitimate and necessary part of continuous improvement activities.

If successful the effect of the experimental treatments outlined in Chapter 3 will impact the experimental learning curves in the autonomous learning region of the learning curve (Figure 2.1).

Theoretical Framework for Individual and Group Continuous Improvement and Organizational Learning

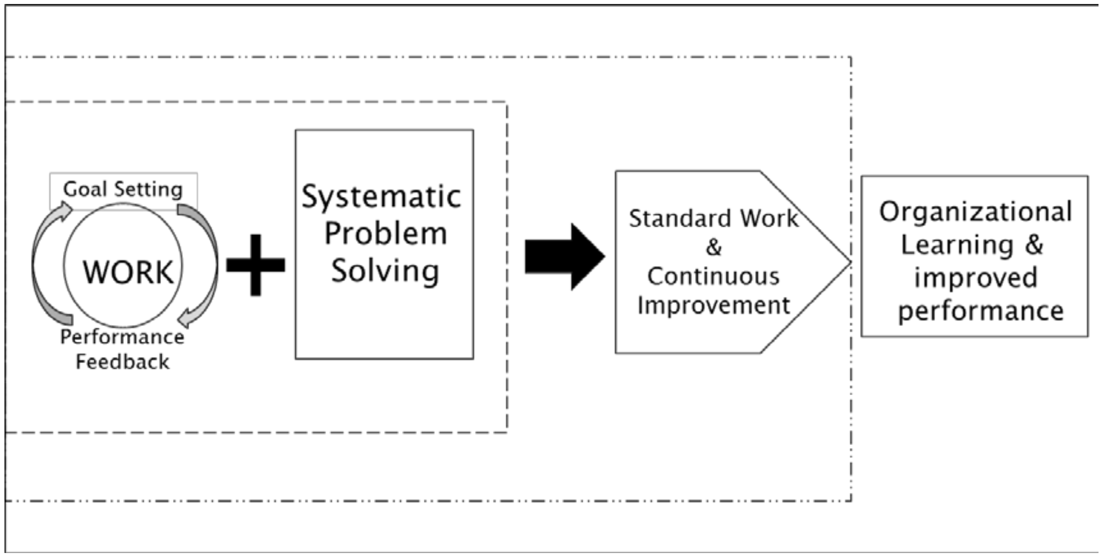

Figure 2.5. Relationship between Intrinsic Motivation Model, systematic problem solving, continuous improvement and organizational learning.

The proposed research hypothesizes the slope of the learning curve in the autonomous region should increase for treated groups. This increase in the learning rate indicates a shift of induced learning into the autonomous region as illustrated by the dotted line included in Figure 2.6. The dotted line in the autonomous region is labeled the “Induced Autonomous Learning Rate” represents the amount of new learning experienced by team members in the experimentally treated teams compared to the expected ”Autonomous Learning rate” obtained from untreated teams.

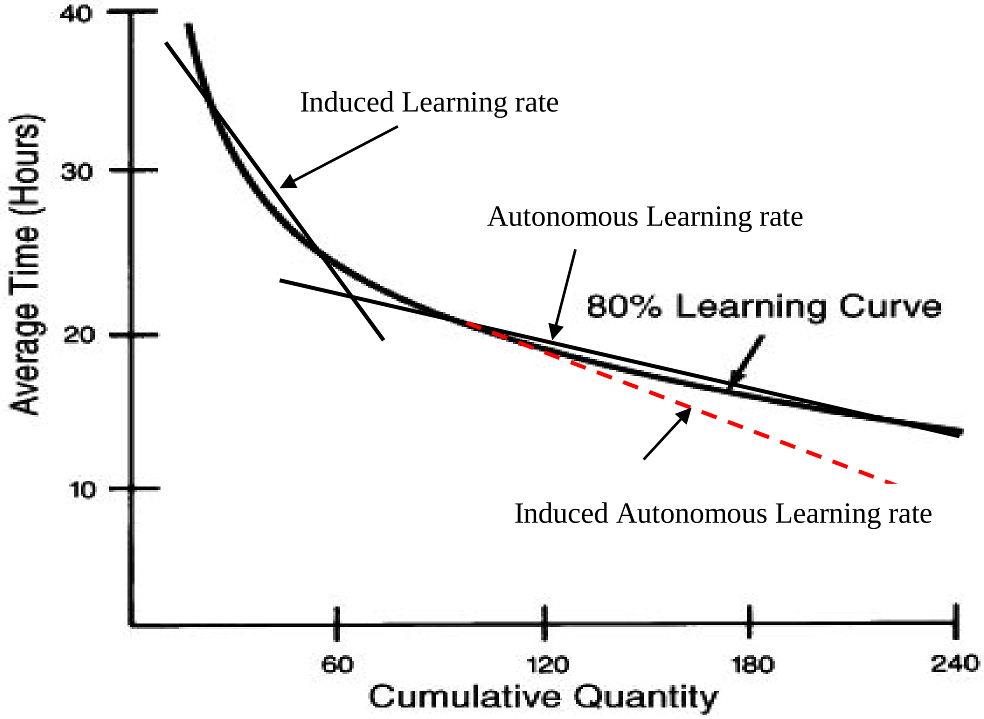

Figure 2.6. Illustration of a learning curve showing Induced and Autonomous learning regions along with the hypothesized Induced Autonomous learning region as the result of systematic P/S at team member /work interface.

CHAPTER 3: EXPERIMENTAL LEARNING CURVE STUDY SET-UP

3.1. Introduction

This study contributes to the mainstream of learning curve and TPS related research by focusing on the effect of specific TPS principles on the learning outcomes of individuals in a controlled environment. By designing an experiment to measure outcomes of individual operators, this study can determine more directly the effects of systematic problem solving activities related to implementing standard work and eliminating waste during the course 256 unit cycles without the inherent 'noise' associated with on-going operational issues such as worker availability, productivity and quality issues, equipment availability and other issues common to most manufacturing organizations. The two-station experimental set-up minimizes the impact of uncontrolled variables and allows for more direct observation and measurement of the operators productivity than is often possible, even in small manufacturing facilities.

The results of these studies could shed light onto why Toyota's operational structure has been so successful in creating and sustaining an environment of continuous improvement, namely that while the adherence to standard work keeps the worker from straying too far from the MTM standard, at the same time, by encouraging workers to always look for waste in their process and by providing a method to eliminate the abnormal work and waste, allows workers to improve their work without requiring burdensome change procedures, enabling each worker to utilize the incremental learning occurring with each performance cycle, resulting in an overall decrease in process time or reduction in errors, ie increased learning.

3.2. Experimental Set-up

The basic experimental set-up is illustrated in Figure 3.1. The set-up will consist of two operators (A & B) located initially at Stations 1 and 2 respectively along with a team leader / observer, depending on whether the team is “treated” or not. The work performed by the operators consists of an assembly operation at Station1 and a quality check, disassembly and material staging operation at Station 2. The double arrows indicate the work will flow in a cyclic pattern between the Stations.

Each team will conduct a total of 4 runs, making 256 cycles (cylinders) per run. CT data will be recorded at the end of each work cycle by the operators as part of their normal work. The work content at each Station is designed to take approximately 30-60 seconds per cycle. At the end of each 16 cycle set, each operator is instructed to complete a brief assessment to obtain qualitative data on: 1) level of engagement, 2) physical burden, and 3) mental burden.

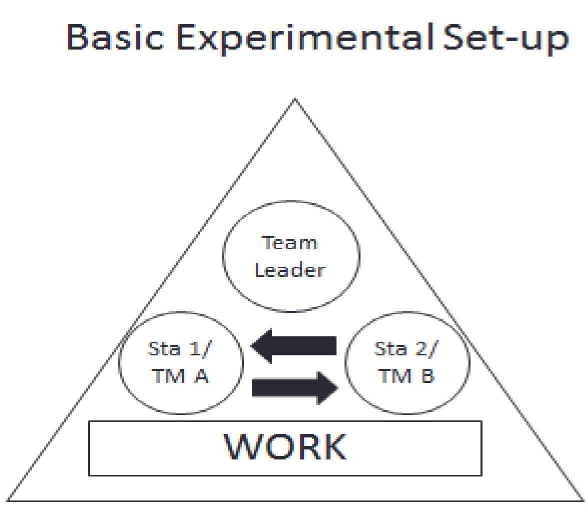

Figure 3.1. Schematic illustration of the basic experimental set-up.

The work will be performed under controlled conditions and involve small teams consisting of two operators and a supervisor/team leader per team. The results from each team will be analyzed to determine the effects of experimental treatment on demonstrated learning outcomes and incorporated into the learning model.

3.3. Experimental Design

The study is based on a 2x1 replicated quasi-experimental design illustrated in Table 3.1 and Figure 3.2. According to Cook and Campbell, (1979) a quasi-experiment is one where treatments are not assigned randomly. Because of the nature of the treatments, and physical and time constrains the experiments were not performed in a totally random order. Due to physical limitations all the experiments were conducted in the same room and time constraints for the students required 2 teams to work simultaneously. However, the teams were situated so that neither team was in direct eye contact of each other. To eliminate confusion and minimize the possibility of one team obtaining extra learning they would not otherwise be exposed to during the normal course of the experiment both teams performed the same set of experiments on the same days. However, the teams were not allowed to collaborate between themselves or share results or other information during the course of the experiments. Teams performed under the same experimental conditions were grouped and ran simultaneously with limited access to each other.

As seen in Table 3.1, all teams will perform runs 1 and 2 under the same conditions. Because the composition of each team was determined by scheduling convenience each team is treated as a non-equivalent group (Cook and Campbell, 1979). Under these conditions treatment affects are compared between the groups based on measurements before and after application of the experimental treatments under conditions presented in Table 3.2. For these experiments runs 1 and 2 serve to develop “experienced” operators in preparation for runs 3 and 4, and help minimize the initial differences between each team. In addition, runs 1 and 2 provide baseline learning curves to be used to compare treatment effects applied during runs 3 and 4.

Table 3.1. Experimental conditions for runs 1 and 2.

Runs 1 and 2 Experimental Conditions (Baseline Runs)			
Run 1 (256 cycles)		Run 2 (256 cycles)	
Station 1	Station 2	Station 1	Station 2
Operator A	Operator B	Operator B	Operator A
Input Variable Settings			
No Job Rotation during Production Run			
Operators Work Independently			
No Standard Work (Perform Normal + Abnormal work)			
No Collaborative Problem Solving			
No Waste Elimination (Yamazumi Thinking)			

Table 3.2. Experimental conditions for runs 3 and 4.

Runs 3 and 4 Experimental Conditions (Treatment Runs)			
Run 3 (256 cycles)		Run 4 (256 cycles)	
Station 1	Station 2	Station 1	Station 2
Operator A	Operator B	Operator B	Operator A
Input Variable Settings			
Job Rotation: Low = 1(at cycle 129)			
R3		R4	
Standard Work (focus on performing normal work)		P/S Obstacles to perform Standard Work (same as R3)	
Collaborative Problem Solving (P/S) to eliminate abnormal work		Waste ID and P/S to eliminate and realign work as needed (including WIP reduction)	

Although there is limited ability to control the personal abilities and other individual characteristics within each team, the laboratory setting allows a more controlled treatment application than would generally be possible in the field. The experimental design is graphically illustrated in Figure 3.2. The figure shows R1 and R2 are performed by all teams under the same conditions, R3 and R4 are the treatment runs in which teams 1 and 4 create and maintain standard work (R3) and reduce/eliminate waste (R4). Both treated teams for R3 and R4 use systematic problem solving.

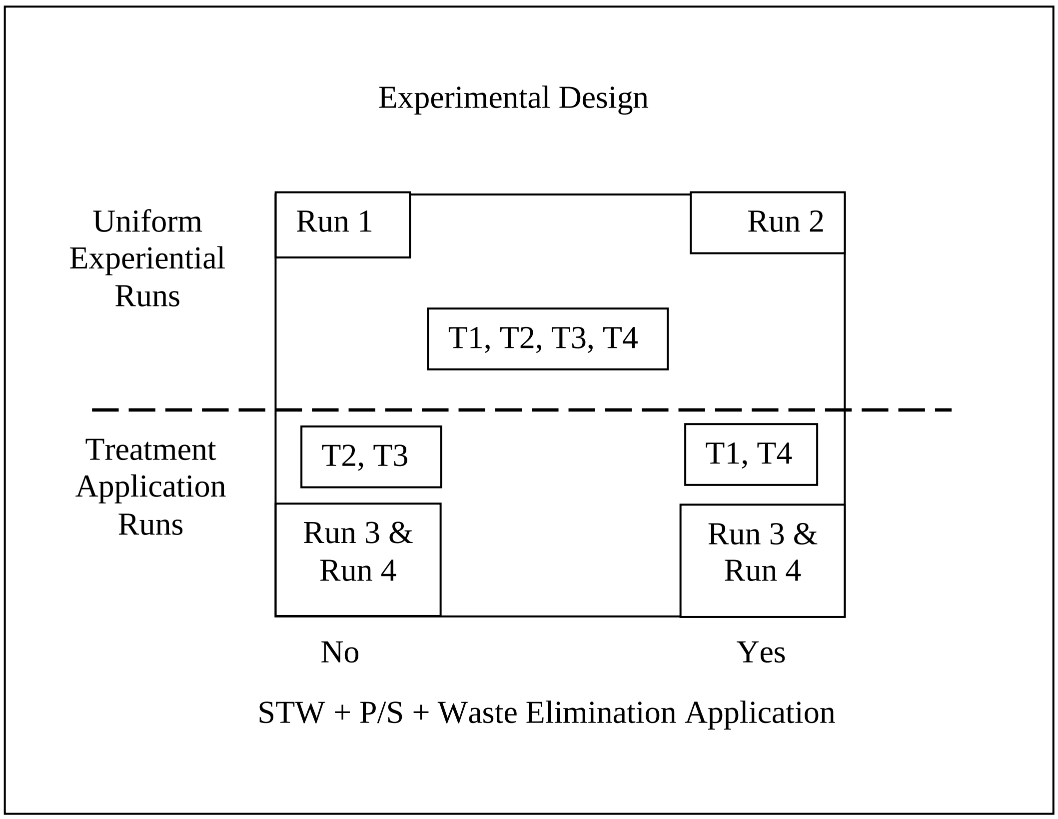

Figure 3.2. Illustration of the experimental design for Runs 1 through 4.

This simple design provides an ability to gather insight into the primary effects of each treatment without potential interference from higher levels of organizational structure (eg. supervisory, other functional areas, HR policy and leadership). As shown in the figure, to help overcome the anticipated variation due to the inherent noncomparability of the teams and the relatively complex nature of the treatments, all experimental runs were replicated as part of the study. The independent variables for the study are systematic P/S to achieve standardization (R3) and systematic P/S to assist in waste elimination (R4). Basic outputs include individual and team cycle time (CT), and qualitative assessment results, including team member attitude, and mental and physical burden.

3.4. Personnel Requirements

Each team consists of 2 operators or team members (TM) plus an optional team leader (TL). Students were used as TMs because of availability and they have fewer preconceptions regarding assembly operations and work organization. There 2 basic experimental conditions tested requiring 4 teams and 12 students.

3.5. Physical Set-up Conditions

A photograph of the products listed in Table 3.3 is presented in Figure 3.3. Using the nomenclature of Table 3.3, the products shown in Figure 3.3 are from left to right, Blue, Red and Green. Each cylinder in the figure sits atop a production card (PC) which must accompany them. Several features seen in the figure are also critical quality characteristics including the holes on each plate must be aligned (i.e., both top and bottom plate holes (ports) are on the same side), the nuts must be tight and the piston must be able to move freely up and down.

Photographs of the experimental set-up for Stations 1 and 2 are presented in Figures 3.4 and 3.5 respectively. Station 1 includes a fixture to tighten the bolts, containers (yellow) for nuts and washers, and a stop watch for measuring individual cycle times. Included in Figure 3.4 are incoming cylinder parts on the nearest table which were created in Station 2 and out-going completed cylinders along with the piston lube on the far table. Also shown in Station 1 are the individual parts for a Red cylinder.

The set-up for Station 2 is shown in Figure 3.5. The figure includes bins for the bolts, various sized tubes, top and bottom plates with O'rings inserted, and small yellow bins for the nuts and washers.

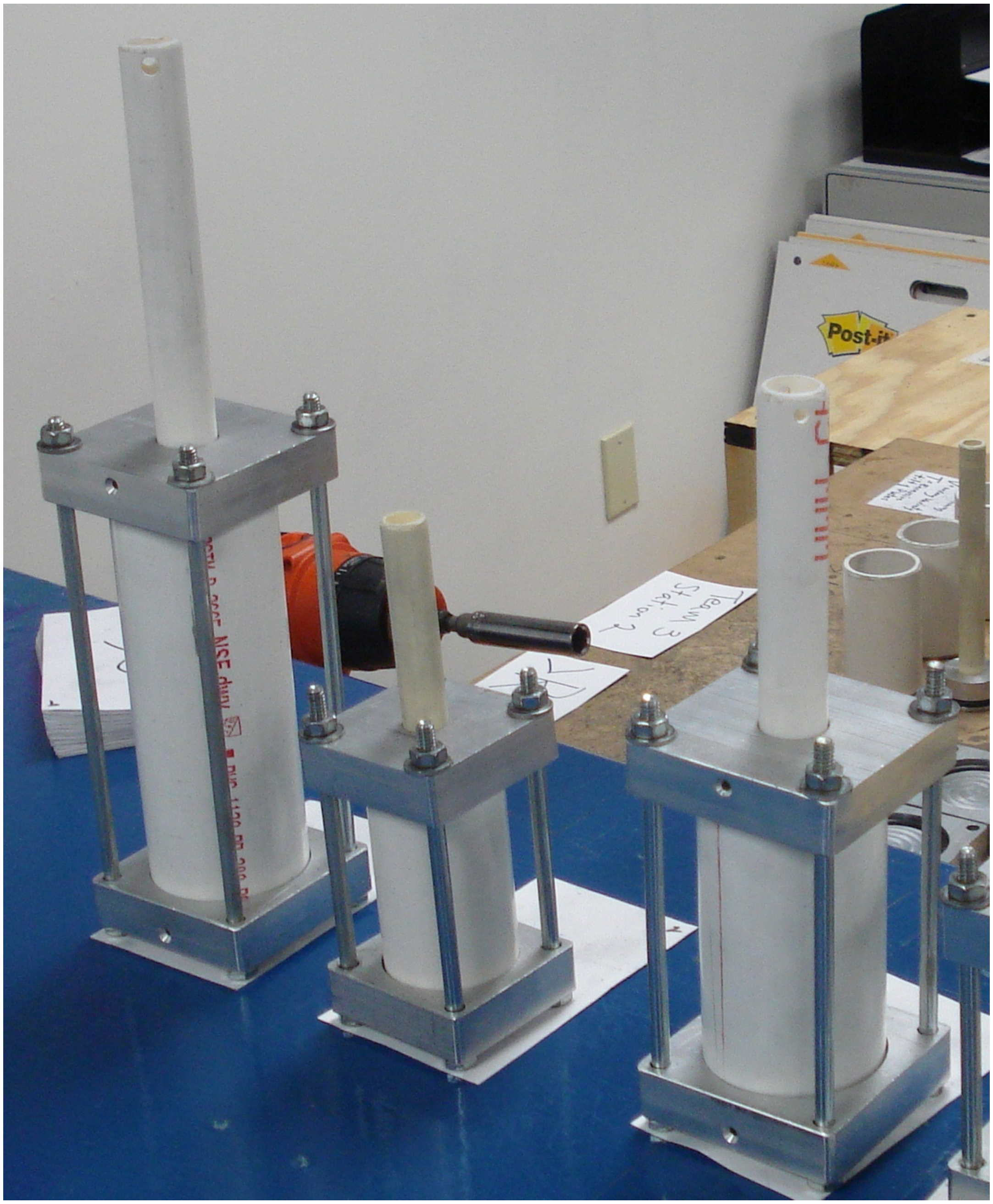

Figure 3.3. Experimental products. From left to right; Blue (large), Red (small), Green (medium).

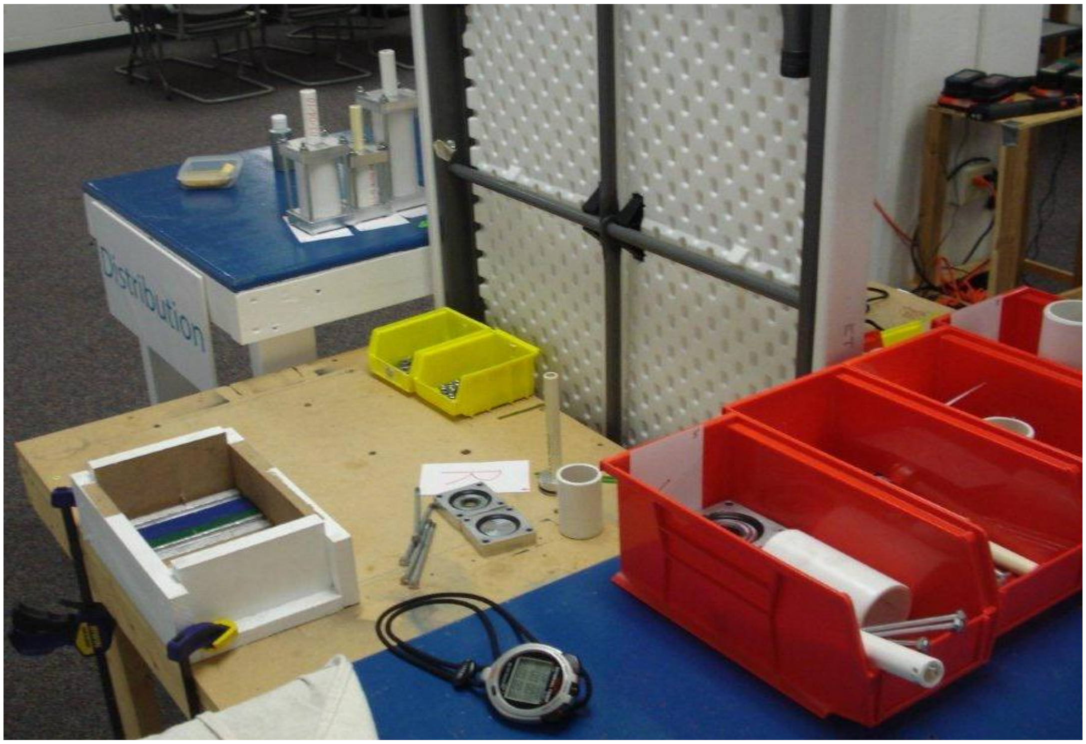

Figure 3.4. Starting set-up conditions for station 1 showing all materials used in this study.

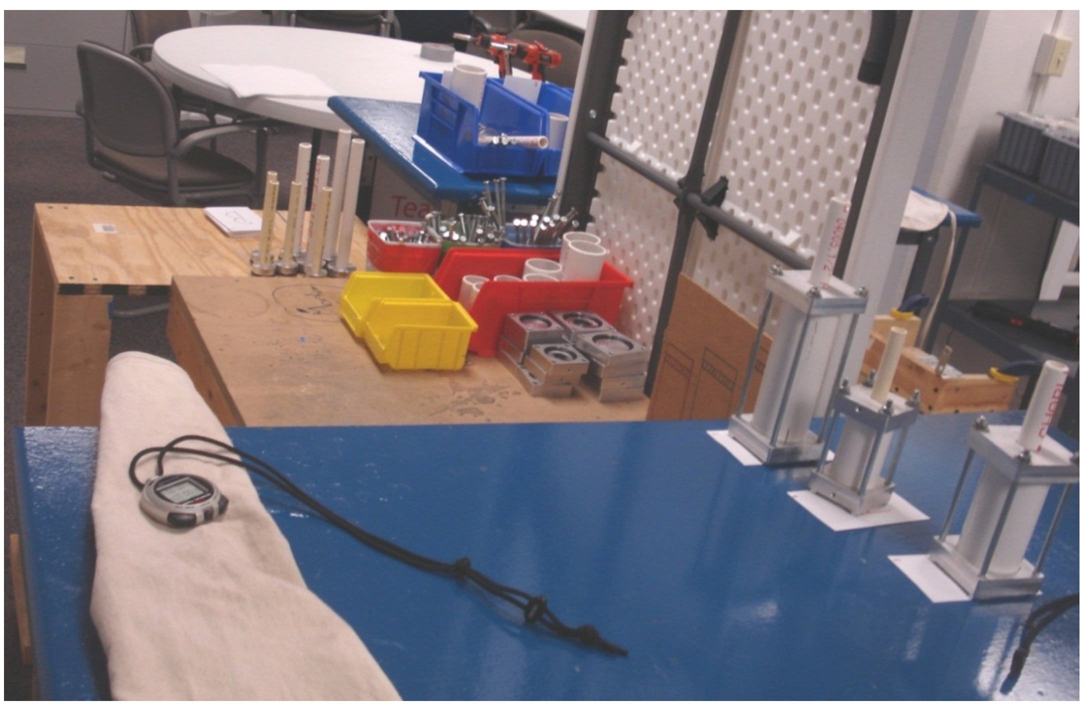

Figure 3.5. Starting set-up for Station 2 showing the hardware and parts used in this study.

Two teams, each with the same treatment conditions, were ran simultaneously. Figure 3.6 shows how they were laid out in the room where the experiments were conducted. The figure shows on cell in the forefront on the left which includes tables for both statins and an additional table for the outputs/inputs for each station. the other cell was located in the back right side of the figure. The table situated in front of the center support pillar contained miscellaneous parts and consumables such as towels and lubricant, and charging stations for the drills along with extra drills.

Figure 3.6. Visual layout of two cell, each consisting of stations 1 and 2 plus additional tables for inputs/outputs.

All experiments were conducted in RM 320 on a 2 Station system designed to build PVC pneumatic cylinders. There were 3 TMs per team. Two TMs were designated operators, one to assemble cylinders (Station 1) and the other TM to perform a quality checks, disassemble and re-supply the assembler at Station 1 (Station. 2). The third TM on each team played the role of observer, and supervisor or TL. Stations 1 and 2 in each cell were arranged be back to back of each other but separated by an opaque divider. Additional space was provided for work in process (WIP between Stations) to provide the opportunity to work independently of each other.

The product consisted of 3 variants of the PVC pneumatic cylinders according to Table 3.3 shown below. Also, both Stations were provided with a stopwatch, individual work cycle time (CT) log sheets and 16 assessment sheets to be used at the end of each 16-cycle set. Station 1was also provided with a fixture to hold the bolt-heads secure while the four nuts on each cylinder are being tightened, and a Craftsmen 7.2 volt battery powered nut driver w/7/16" socket preset at torque level 12 (determined by counting clicks on the setting spindle since the level indicator is not fixed) at the Hi speed setting.

Table 3.3. Product codes and characteristics.

Product Code	Relative Tube Length	Tube Diameter (inches)
Red	Short	1.5
Green	Medium	2.0
Blue	Long	2.0

Station 2 did not have a fixture to remove the nuts but is provided with a 14 v Black and Decker Stationary pistol nut driver and 7/16" socket preset to Hi Torque and number 2 speed setting. Both Stations have an additional pre-set driver, sockets, extra charged batteries and battery chargers available nearby. Safety glasses are to be worn during each run. Initially written work instructions are provided in the form of an SOP describing the work elements in general and specifying when to lap their stopwatch to obtain consistent cycle times for each experimental condition. Each operator was shown the work and allowed to perform it once before actual timed cycles begin.

3.4. Experimental Run Conditions

1. Each experiment consists of a total of four runs (one run per day) per team

2. Each run lasts 8-10 hours and consists of building 256-unit cycles, with a quality assessment and reset activities performed between each 16-unit cycle set.

3. Experimental run 1 and 2 were conducted on consecutive days and all runs 1 and 2 were completed in the first week. There was a lay-off of approximately 7 days between the end of run 2 and the beginning of runs 3 and 4.

4. Run conditions remained constant for runs 1 and 2 for all 4 experimental teams.

5. All operators for run 1 switched Stations for run 2. Otherwise there was no job rotation in R1 and R2.

6. Operators A and B on both the treated and untreated teams rotate their jobs at cycle 128 (the midway point of the run) for R3 and R4.

3.6. Initial Experimental Set-up Conditions: (R1 and R2)

1. Each student operator is assigned and trained on a specific operation in the cell. Once assigned, the student performs the same operation on each unit produced. Training consists of facilitator walking thru and demonstrating the jobs and allowing the student to perform the job once.

2. The student operators perform any task needed to complete each unit.

3. Each operator collects and records individual cycle time of their process and tracks defect (Station 2 only) as part of their regular tasks for each unit cycle.

4. The third student acts as an observer/supervisor to monitor team actions to ensure compliance with the rules and chart the results as each 16 cycle set is completed.

3.7. Problem solving (P/S) conditions

P/S = 0: The P/S = 0 condition is equivalent to the base line conditions present for all teams in R1 and R2. Operators performing under this condition work independently of each other and do not participate in collaborative systematic problem solving. There is no obligation for either operator to perform their work in the same manner. The idea of separating normal and abnormal work is not introduced and therefore no systematic problem solving occurs aimed at eliminating obstacles to performing normal work. The Starting condition for R3 in each Station is the condition of the last operator at the end of R2. Each operator is free to adjust their Station and work sequence to suit them at the beginning of R3 and R4 as well as when the operators rotate. Problem solving will take place under uncontrolled conditions using non-systematic methods in the sense each operator is allowed to problem using any method they are comfortable, including generic, generalized problem solving. As in R1 and R2 operators are encouraged to identify problems and develop work-a-rounds to compensate. There is no formal training on Standard work, systematic problem solving or waste identification and elimination. For experimental runs with P/S=0 operators will not be encouraged to share ideas, however, there are no repercussions if they do. This includes operators on different teams. Because the operators do not have Standard work, they are also not trying to balance their work. WIP remains at 4 between each operator for R3 and R4 to allow operators to continue to work independently.

P/S = 1: This condition includes treatments phased in during R3 and R4. In R3 the operators use Standard work created by the last Station operator at the end of R2. At the beginning of R3 the operator is coached to follow it. Before beginning R3, team members are introduced to Standard work and 8-step problem solving. As a condition of R3, their participation in collaborative systematic P/S activities designed to eliminate obstacles to performing Standard work is encouraged and facilitated by an 8-step problem solving trainer. In effect, this focuses P/S activities on eliminating abnormal conditions relative Standard work. In R4 operators are trained to identify waste and encouraged to eliminate it using collaborative problem solving. Because excess work in process (WIP) represents waste in the system, both R4 treatment runs start with WIP = 4 but experience WIP reduction to 2 at cycle 32 and 1 at cycle 194, where it remains for the rest of the run.

CHAPTER 4: DATA COLLECTION & ANALYSIS

4.1. Data Collection

1. Individual unit cycle time (CT) data is recorded as part of both operators' Standard operating procedure. The CT will be digitized and used create individual and team learning curves (LCs).

2. An assessment form is completed following each 16-unit cycle listing problems encountered, work-a-rounds developed, potential causes (focused on the work performed at each Station), and suggested countermeasures (CMs), identified as short term and long term.

NOTE: Only short-term CMs will be implemented (if possible)

Included in the 16-cycle assessment form are requests to rate the operator's level of engagement (1 = bored to death, 5 = fully engaged), physical burden and mental burden separately (1 = very easy , 10 = very difficult).

4.2. Data Analysis

Individual cycle time (CT) data obtained from each team member in both treated and untreated team will be used to generate LC constants (LCCs) as the unit of measure for comparative quantitative analysis. The quantitative analysis will evaluate resultant LCCs from four perspectives:

1. Individual team members (TM or operator for individual runs),
2. Combined CT data (same operator at both Stations and same Station using both operators for individual runs),
3. Contextual CT data (individual or combined CT data as part of 4 run total cycles), and

4. Coupled CT data (total cycle time (TCT) or throughput time (TPT) of both Stations with and without wait time included).

Cycle time data from each operator will averaged in 8-cycle bundles or sets to reduce the amount of "noise" in the resultant LCs.

The primary experimental outcome of this research is to explicitly investigate the impact of systematic problem solving supporting standardization and waste elimination on both individual and team learning and use the results to create a predictive probability continuous improvement learning model. The model will be "calibrated" based on the results from learning curve analysis of experimental data associated with operator, station and team or "system" performance.

Group-to-group analysis will involve dividing the 4 teams into two groups based upon whether or not they received treatment in R3 and R4. Cycle time (CT) data collected during each run will provide the basis for learning curve analysis.

4.3. Learning Curve Coefficient Analysis

In this section cycle time (CT) examples of data from the learning curve experiments will be presented and the method used to analyze them is described. An example of each condition is presented along with the best-fit trendline and power law equation associated with the curve. Learning curve coefficients (LCCs) are obtained directly from the exponent of the power law equation. The CT data is presented in graphical format as individual learning curves. The goal of the first section is to explain the basic unit of measure used in the study and to describe how the LCCs are obtained.

The basic form of the learning curve is a power model and can be expressed as:

$$CT(n) = CT(1) \times n^{-b} \qquad (4.1)$$

Where $CT(n)$ is the current cycle time or cycle time of a specific cycle, $CT(1)$ is the cycle time of the first cycle performed, n is the number of cycles and b is the learning constant (Dar-el, 2000). The learning constant (LCC) is determined directly from the experimental data and will be the initial unit of measure for this study.

Traditionally learning is also expressed as the percent of the learning slope (Φ) or learning rate, which in this study defines the percentage of the CT remaining with each doubling of cycles. That is, for $n_2 = 2n_1$, the constant percent of reduction in CT can be expressed as (Globerson, 1980):

$$CT(n_2) / CT(n_1) = CT(2n_1) / CT(n_1) = (CT(1)\times(2n_1)^{-b}) / (CT(1)\times(n_1)^{-b}) = 2^{-b},$$

and

$$\Phi = (2^{-b}) \times 100 \qquad (4.2)$$

Where Φ is the percent learning rate (LR) based upon changes with CT and b is the experimentally obtained LCC discussed above. The larger the value of Φ the less the actual learning rate occurring.

Although the value of Φ is implicitly thought of as the difference of the calculated Φ from 100, it can be confusing for readers not involved directly in learning curve research. To reduce confusion a new term is introduced called the *demonstrated learning constant (DL or* Ψ*).* Equation 4.3 shows the relationship between the LCC (b), the learning rate (LR or Φ) and the demonstrated learning Ψ.

$$\Psi = (1 - 2^{-b}) \times 100 = 100 - \Phi \qquad (4.3)$$

The value of Ψ measures the amount of learning occurring as indicated by observed experimental cycle times in the area of interest, the larger the value of Ψ, the greater the demonstrated learning in the system.

4.4. Experimental Design

The experimental conditions illustrated in Figure 3.2 represent the treatment settings for systematic P/S for standard work and waste elimination. In addition to the LCC output data used in previous analysis, this analysis will also use the results of an assessment questionnaire completed as part of the 16-cycle assessments mentioned in the previous chapter as input for the probability model introduced below.

4.5. Predictive Probability Continuous Improvement Model

A probabilistic model has been created to illustrate the effects of the independent variables on the likelihood of creating a sustained continuous improvement capability. The model is shown in Figure 4.1. State 1 represents the experimental conditions for R1 and R2 where the operators or team members are supposed to do their work the best they can, are motivated to increase productivity as much as possible and conduct unstructured P/S activities to eliminate problems. In addition they are performing both normal and abnormal work as part of their Standard work routines. State 2 represents R3 where team members have created Standard work and are conducting systematic P/S to eliminate abnormalities preventing them from performing normal work. State 3 represents R4 where team members are again conducting systematic P/S to support Standard work, but are also focusing on using systematic P/S to eliminate waste. State 4 represents a stage were a robust system to support the application of systematic P/S for Standard work and waste elimination working together to maintain current Standard conditions and create incremental continuous improvement. State 4 represents the true lean condition in which companies are capable of conducting spontaneous Kaizens at the shop floor.

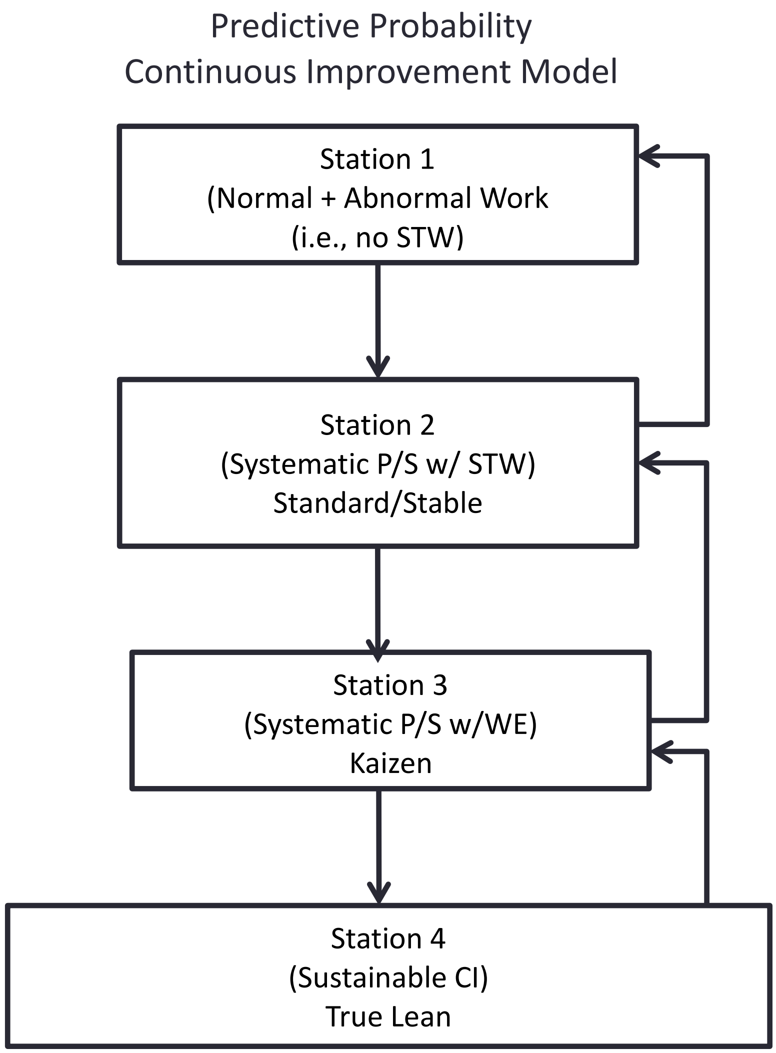

Figure 4.1. The predictive probability model to calculate the probability of creating a successful CI environment based on LC results.

The LCs obtained from the experiments provides the basis to calibrate the level of learning achievable in each state at the TM/work interface. Because the experiments were designed and executed with only the team leader function in place, the learning measured represents an approximate best case under those conditions. There are no higher organizational levels which could possibly distort or reduce the effectiveness of the learning environment.

Activities surrounding the development of a sustainable continuous improvement environment within organizations are essentially similar to conducting a lean transformation. Therefore the subjective probabilities of moving from state to state were determined using the most often cited success rate for lean transformations in the literature. Table 4.1 is the transition matrix showing the probabilities of moving from one state to another. The initial probabilities shown were selected to result in a steady state of approximately 25%, which is roughly equivalent to some estimates of the success rate for companies implementing lean (SME Survey, 2005). In this study, attaining a continuous improvement environment is synonymous to achieving a true lean condition.

Table 4.1. Initial state to-from probability transition table.

From	To			
	State 1	State 2	State 3	State 4
State 1	0.965	0.035	0	0
Sate 2	0.04	0.925	0.035	0
State 3	0	0.04	0.925	0.035
State 4	0	0	0.04	0.96

Initial assumptions for the model include;

1) The model is a closed system with a population of 100 units (companies), all starting in State 1 at time (T) = 0.

2) The initial steady state distribution of the 100 companies is 25% for each state.

3) The initial transition probability is weighted using the experimentally derived learning ration (LR).

4) Companies can only fall back one state, stay in their initial state, or go forward one state in any 1 cycle.

5) A successful sustainable continuous improvement (CI) environment cannot be achieved without going through both State 2 and State 3 in order.

6) Experimental treatments represent the best case results for those conditions.

Figure 4.2 is a graph of the model output based on the initial conditions outline above showing a steady state condition for State 4 with a LR = 1 at 20 %. A LR = 1 is represents an organization in which CI and or Kaizen activities are being performed, but are generally management directed activities, and result in little or no permanent standardization. As a result, the improvements made often fall apart over several months or years. This condition matches the most commonly referred success rate of 20% for a lean transformation, or an 80% probability of failure under the conditions defined in R1 and R2.

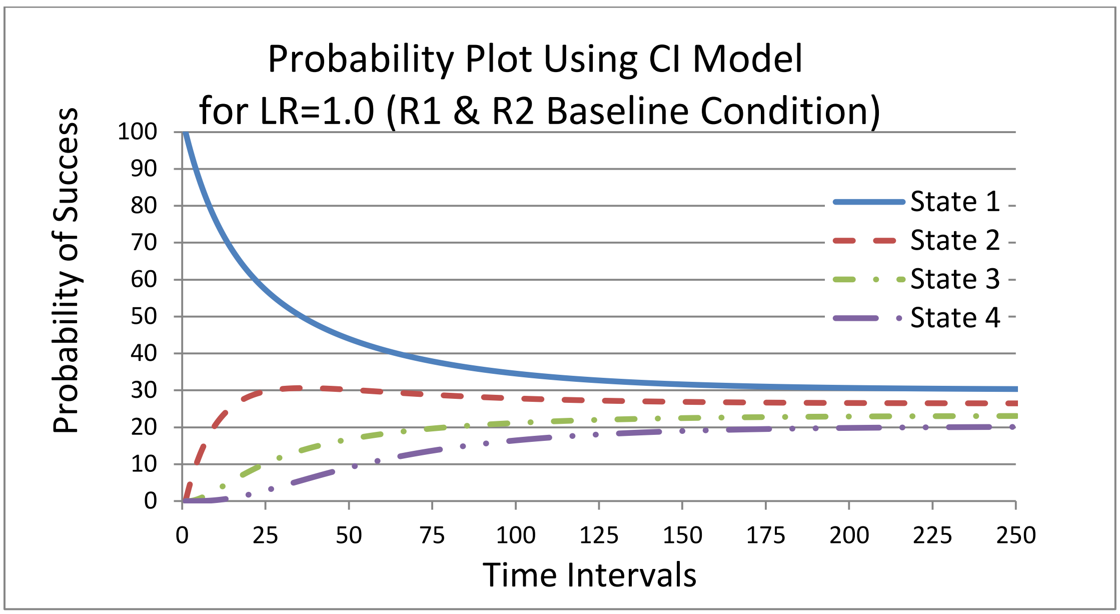

Figure 4.2. Probability plot of baseline conditions for R1 and R2 using the predictive CI model.

The success rate given as an output in Figure 4.2 also corresponds to the approximate failure rate reported by Lapre et al (2000) regarding the success rate of quality improvement projects in their study. The graph also shows the likelihood or probability of an organization being in the other 3 states based on the model, however these cannot be sustained from the available literature. Using the plot in Figure 4.2 as a baseline and LCC data obtained from treated teams in R3 and R4 to represent best case scenarios for the STW and WE conditions, it is possible to construct probability curves to estimate the likelihood of success for an organization to achieve a sustainable CI environment based on the development of systems and behaviors capable of supporting the conditions explored in the R3 and R4 treatments. The final part of this study involves the creation of a relatively simple assessment tool which can be used to determine which state an organization currently resides in, calculate a LR based on the responses and then determine the probability of their successfully achieving sustainable CI capability.

Figures 4.3 through 4.7 are examples of the output of the model based upon learning ratios of 2.5, 5, 7.5 and 10 for all four states.

Notice the difference in the steady state percentage for developing a successful CI environment (State 4) in each graph and the cycle in which it is achieved. As the LR increase, the probability of an organization residing in States 2, 3 or 4 at equilibrium increases while the time or number of cycles required to achieve equilibrium decreases. The equilibrium rates for each state as a function of learning rate were determined from the figures and are presented in Table 4.2 along with the projected approximate equilibrium cycle number.

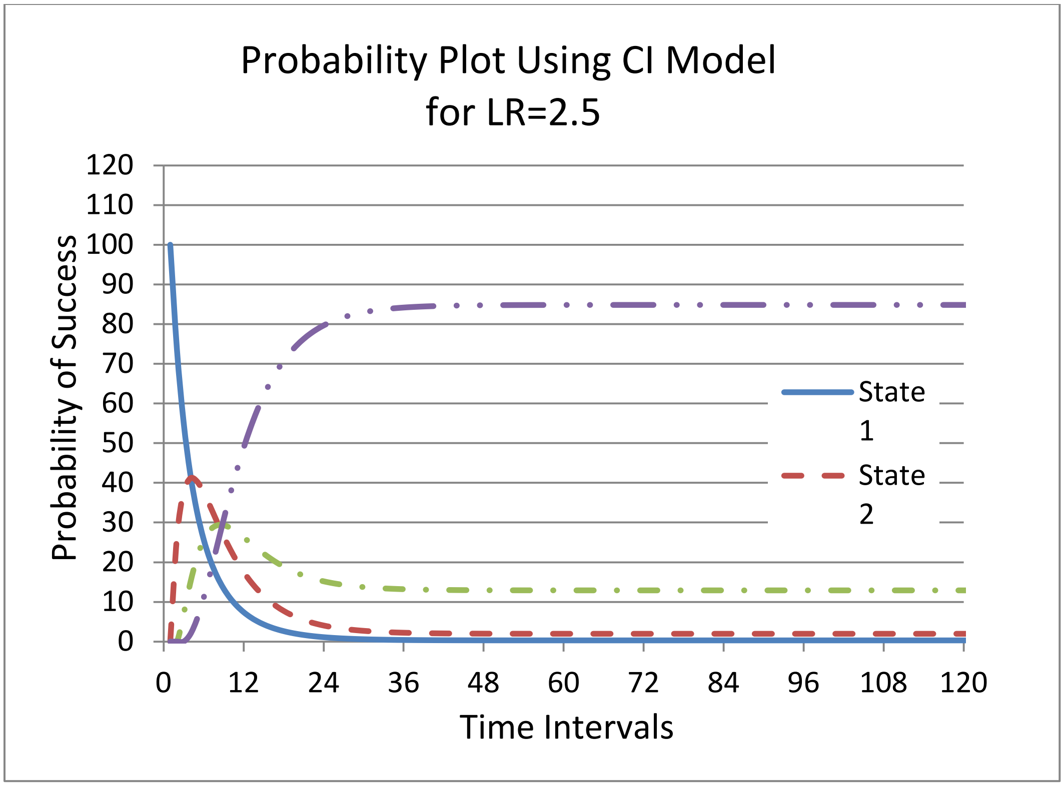

Figure 4.3. Probability plot for LR = 2.5 using the predictive CI model.

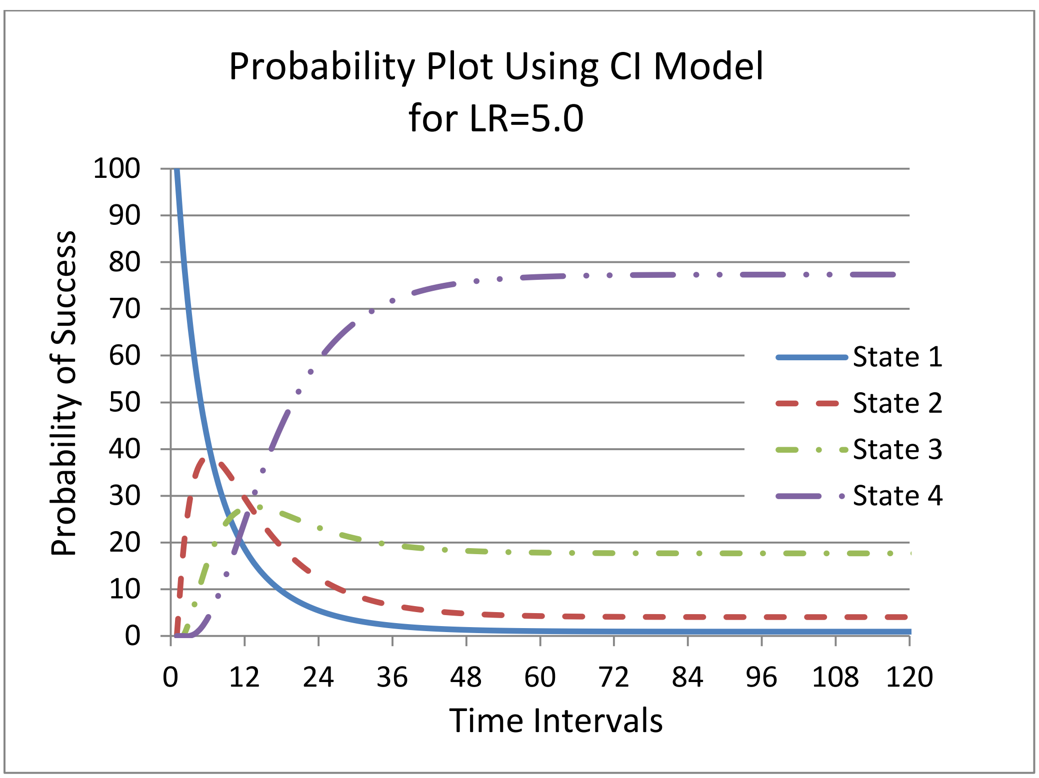

Figure 4.4. Probability plot for LR = 5.0 using the predictive CI model.

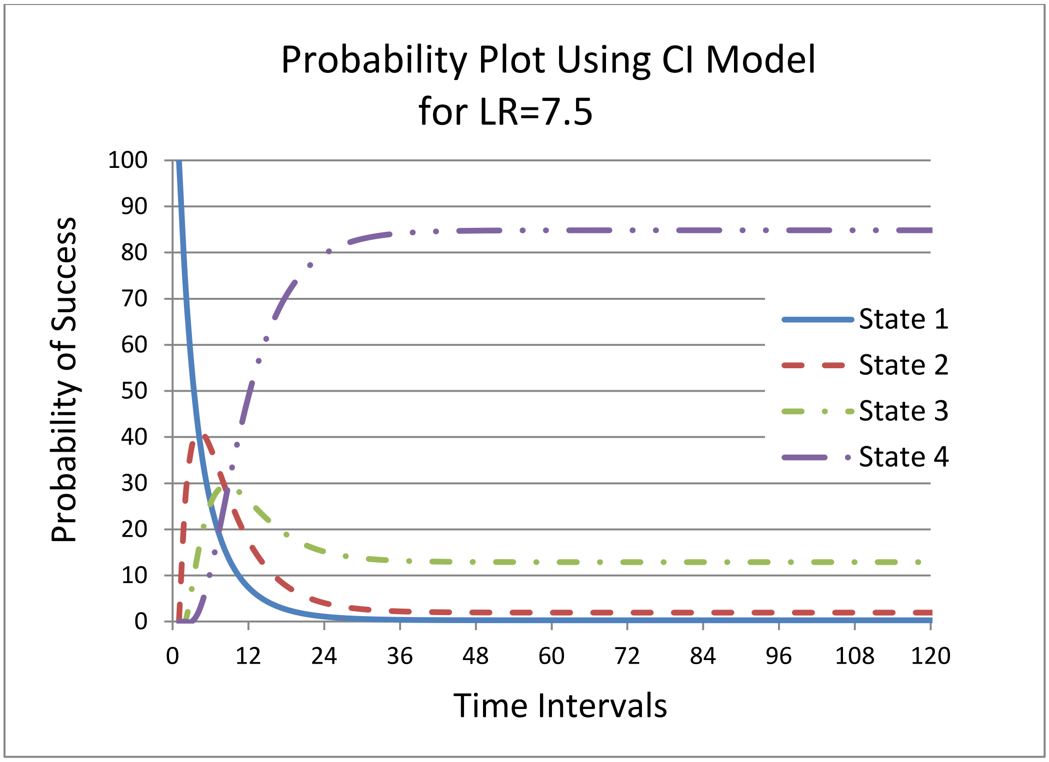

Figure 4.5. Probability plot for LR = 7.5 using the predictive CI model.

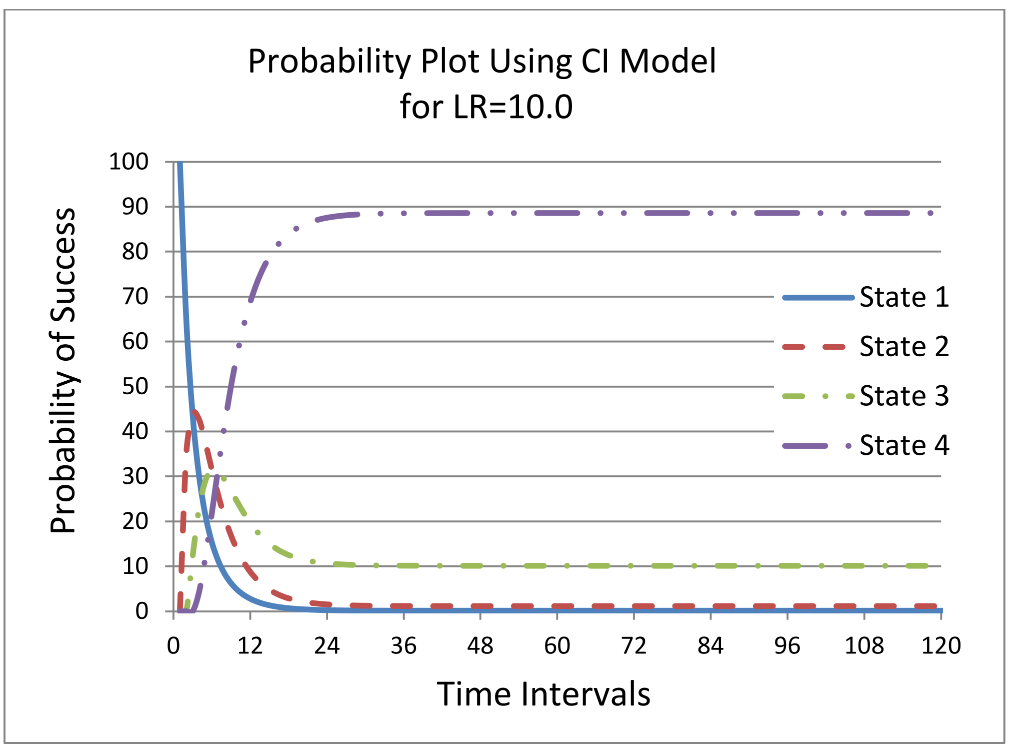

Figure 4.6. Probability plot for LR = 10.0 using the predictive CI model.

Table 4.2. Approximate equilibrium probability for States 1 through 4.

	Approximate Equilibrium Probability at Time Interval (Cycle) X				
Run Condition	**LR***	**State 1/ Cycles**	**State 2/ Cycles**	**State 3/ Cycles**	**State 4/ Cycles**
R1+R2	1	20 / 200	23 / 200	26 / 200	30 / 200
	2.5	5 / 120	12 / 120	27 / 48	56 / 120
R3	5	1 / 72	4 / 72	18 / 50	77 / 72
	7.5	0 / 36	2 / 36	13 / 36	85 / 48
R4	10	0 / 24	1 / 36	10 / 30	88 / 30

*the ratio of LCCs from treated team over untreated teams.

The model output for State 4 is particularly valuable since it represents the true lean or sustainable continuous improvement condition. According to this study, State 4 represents the condition where the capability of sustaining continuous improvement activities based on systematic problem solving to achieve and maintain Standard conditions and eliminate waste are performed without management intervention throughout an organization. Figure 4.7 illustrates graphically the probability of residing in State 4 as a function of LR and cycle number (time). The plots shown in the Figure 4.7 show only the State 4 data along with all four states graphed in Figures 4.2-4.6. However, the scale of the horizontal axis is from 0-250 cycles in order to see the behavior of the LR = 1 condition until it reaches equilibrium. The equilibrium points of from each data set in Figure 17 is represented in the far right column of Table 4.2. If we assume each time cycle to be equivalent to a month, the figure indicates that even after 10 years, the success rate for achieving State 4 is fewer than 20%, approximately corresponding to the commonly cited success rate of 20% for the past 25 years.

Because each state in the probability model represents a significant change in thinking and behavior, led by the use of systematic P/S instead of the more commonly used unstructured methods, the model output for State 4 indicates that even companies specifically targeting Kaizen activities and writing standard work for their processes will only achieve the 20% success mark without changing the learning environment for the TMs (i.e., P/S method, support structure and effective goals-performance feedback loops) at the TM/Work interface.

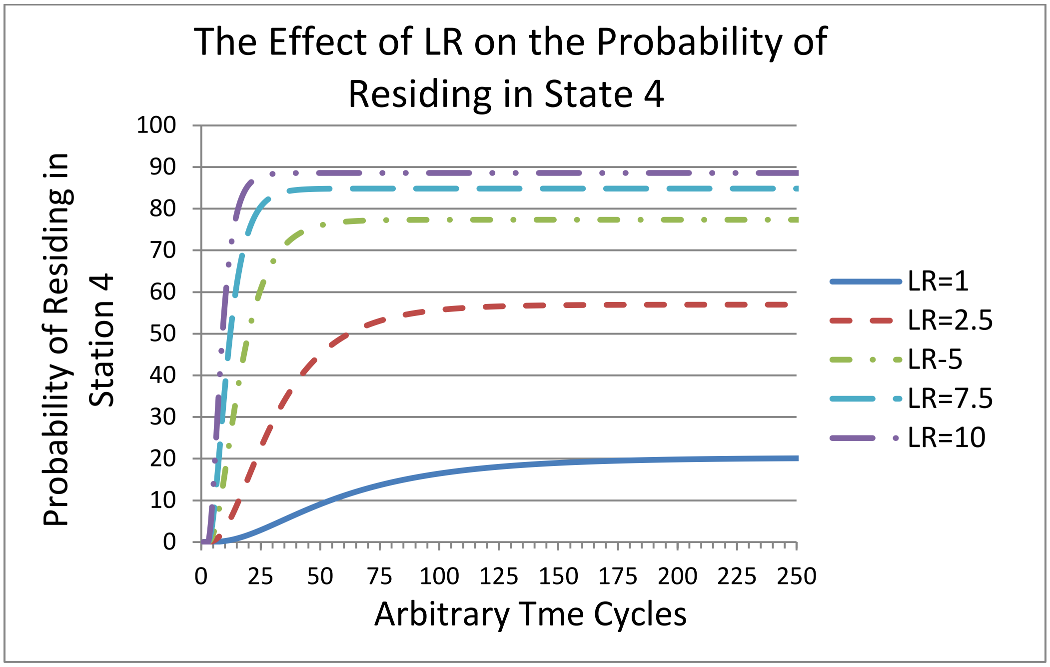

Figure 4.7. The effect of LR on State 4 residency for 250 cycles

Figure 4.8 is a subset of Figure 4.7. It shows the expected chances of organizations reaching State 4 over a 5 year (60 cycles) period as a function of LR. The probability of success varies from approximately 10% for companies in the R1& R2 conditions with a LR=1 up to 88% for companies with a LR = 10. For a company to have a LR of 10 is most likely not possible, however this illustrates the point that there is always some probability of failure, even for organizations with extremely high learning rates.

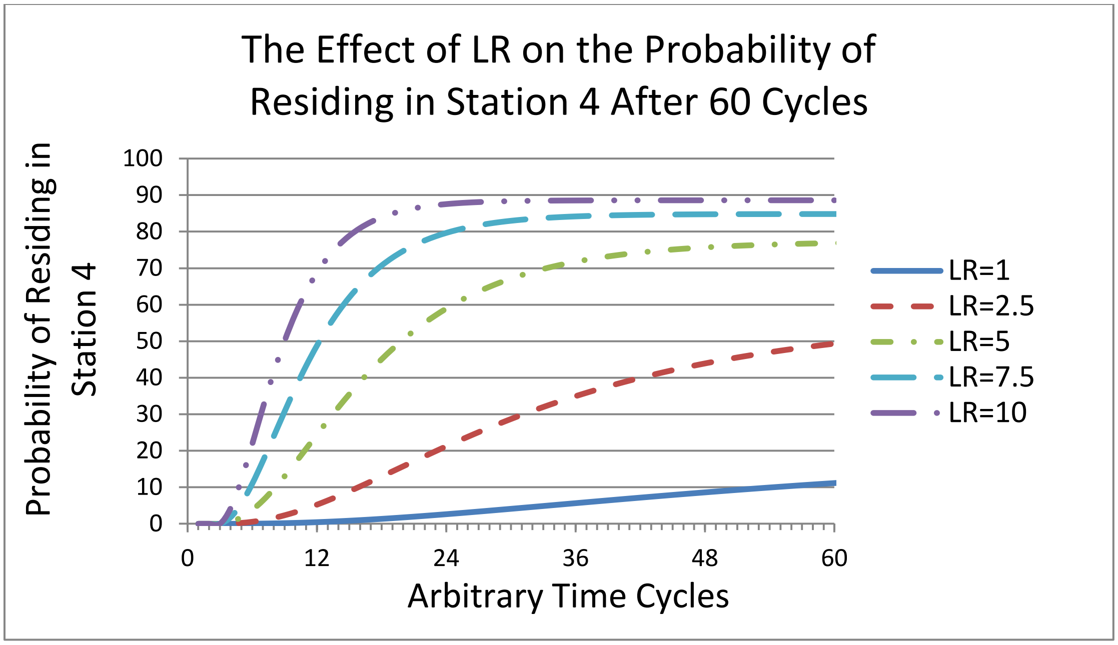

Figure 4.8. The effect of LR on State 4 residency probability over 60 cycles.

The projected probability of residing in a particular state as a function of LR is shown graphically in Figure 4.9 for 24 cycles (T=24) and summarized in Table 4.3. The graph clearly shows how increasing the LR leads to significantly increased probabilities of residing in higher states. It is intuitively reasonable to assign a time frame to T=24 of 24 months and the 24^{th} cycle is the point where LR=10 for State 4 reaches equilibrium as seen in Figure 4.7, representing the fastest possible lean transformation for the model. This means that after 24 months of TMs and TLs working together using systematic problem solving to address problems to perform and improve STW and to eliminate waste, there is an 88% probability appropriate management and other system elements will be in place. This should allow a rigorous PDCA culture to be sustainable for a LR =10, which is the best possible LR. LR=1 means the learning rate (LCC) remains constant over time compared to a sustained increase in learning rate associated with TM learning on the shop floor due primarily to the use of Standard work and systematic problem solving.

Table 4.3. Data from an example application of the model using LRs = 1, 5, and 10 corresponding to conditions tested in runs R1 through R4 of the research.

The Probability of Residing in a Given State at T=24 Cycles				
LR*	State 1	State 2	State 3	State 4
1	58	27	12	3
1.5	43	32	17	8
2	32	33	20	15
2.5	23	32	23	22
3	17	28	25	31
3.5	12	24	25	39
4	9	19	26	47
4.5	7	14	25	54
5	5	10	24	61
5.5	4	7	22	67
6	3	5	20	72
6.5	2	4	18	75
7	2	4	16	78
7.5	1	4	14	81
8	0	5	13	82
8.5	0	6	11	83
9	-1	6	10	84
9.5	-1	5	10	86
10	0	1	11	88

*the ratio of LCCs from treated team over untreated teams.

Based on the experimental results of this study, depending upon the difference in learning as the result of new behaviors and system conditions, the LR could range from 1 up to as high as 7. According to the model (see Figure 4.9), in an organization with no change in TM learning, (i.e., LR=1), there is a 58% probability that organization will still be in State 1 after 24 months, even if they conduct "Kaizen" events, since the conditions of State 1 include only management driven improvement activities. Under those conditions, there is only a 3% chance of reaching State 4 (sustainable CI)

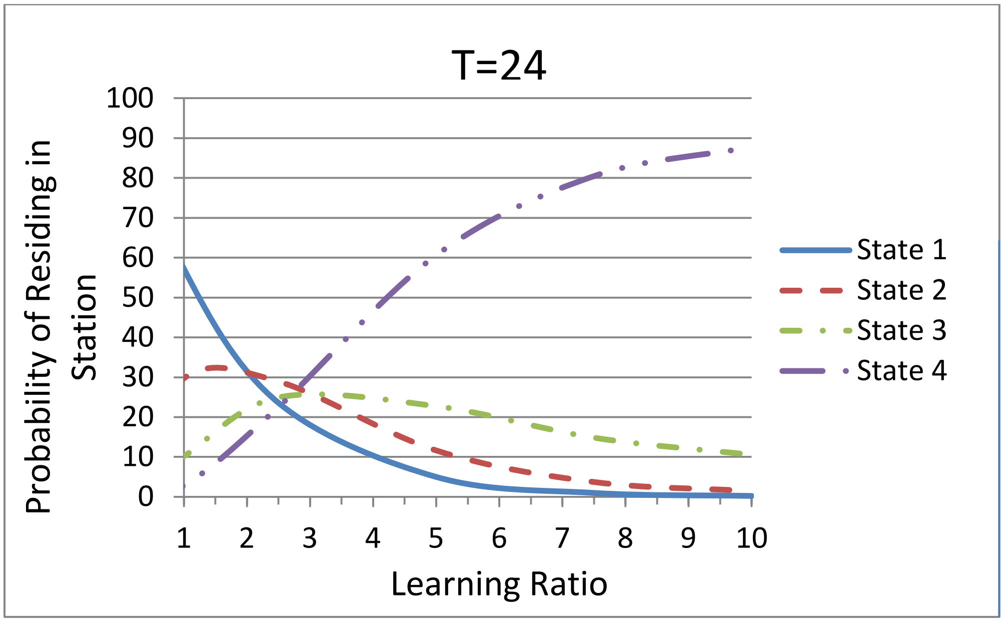

Figure 4.9. Probability of state residency based on LR.

after 24 months. For a LR = 1 there is a much better chance (30%) of reaching State 2 within 24 months since establishing Standard work and systematic problem solving is the first step towards State 4 and could be initiated at any time. Achieving State 3 with LR = 1 is more difficult and less likely (10%) since it requires the ability to support and maintain TMs focus on performing only normal work (i.e., Standard work) before State 3 can be reached. At a LR of approximately 2.5, there is nearly an equal chance of residing in all four states after 24 months. The experimentally derived LCC data will be used to ID specific LRs associated with States 2 and 3. Using Figure 4.9, it will be possible to estimate the probability of successful transformation to a sustainable CI condition (State 4).

CHAPTER 5: RESULTS AND ANALYSIS OF THE EXPERIMENTAL LEARNING CURVE STUDY

5.1. Background

This chapter is broken into six main sections. Section 5.1 involves the analysis of the learning curve results obtained from the first two runs (R1 and R2) which were performed under the same conditions for all teams. Section 5.1 is broken into 3 sub-sections. In sub-section 1, the correlation coefficients (R^2) values associated with excel 2010 program power equation trendlines will be compared.to determine an appropriate data set size for all subsequent analysis. Once the data format is determined in Section 5.1.1, in Section 5.1.2 the LCC results from individual operators consisting of all 256 cycles and of only the least 128 cycles will be statistical analyzed to determine the most suitable data to use in subsequent analysis. And finally, in Section 5.1.3 the resultant R1 and R2 LCC data from all 4 teams will be tabulated for use as the baseline for comparative analysis of the effects of subsequent treatments introduced in R3 and R4. Section 5.2 will focus on the results of individual LC analysis from R3 and R4 and their relationship with the R1/R2 results. In Section 5.3 contextual LCC results obtained from combined learning curve analysis of all the runs will be presented. Section 5.4 will look at both LCC and cycle time (CT) results from the combined data from both Stations to examine the total cycle time (TCT) and total throughput time (TPT). In Section 5.5 the defect data and qualitative results obtained from the 16-cycle assessments during each run will be presented and analyzed. Finally, Section 5.6 will examine the composite contextual LCC results for use as the basis of the predictive probability model introduced in Chapter 4.

5.2. Analysis of R1 and R2 LCC Results

5.2.1. Comparative Evaluation of 1-Cycle, 4-Cycle and 8-Cycle Set CT Data from R1

Figures 5.1, 5.2 and 5.3 show examples of the individual learning curves (LCs) obtained from individual CT and the average of 4-cycle and 8-cycle sets of individual cycle times (CTs) respectively. Each figure contains a trendline for the power law and includes the trendline equation and correlation constant for it. The three figures illustrate the difference between single point data and averaged 4 and 8-cycle point data.

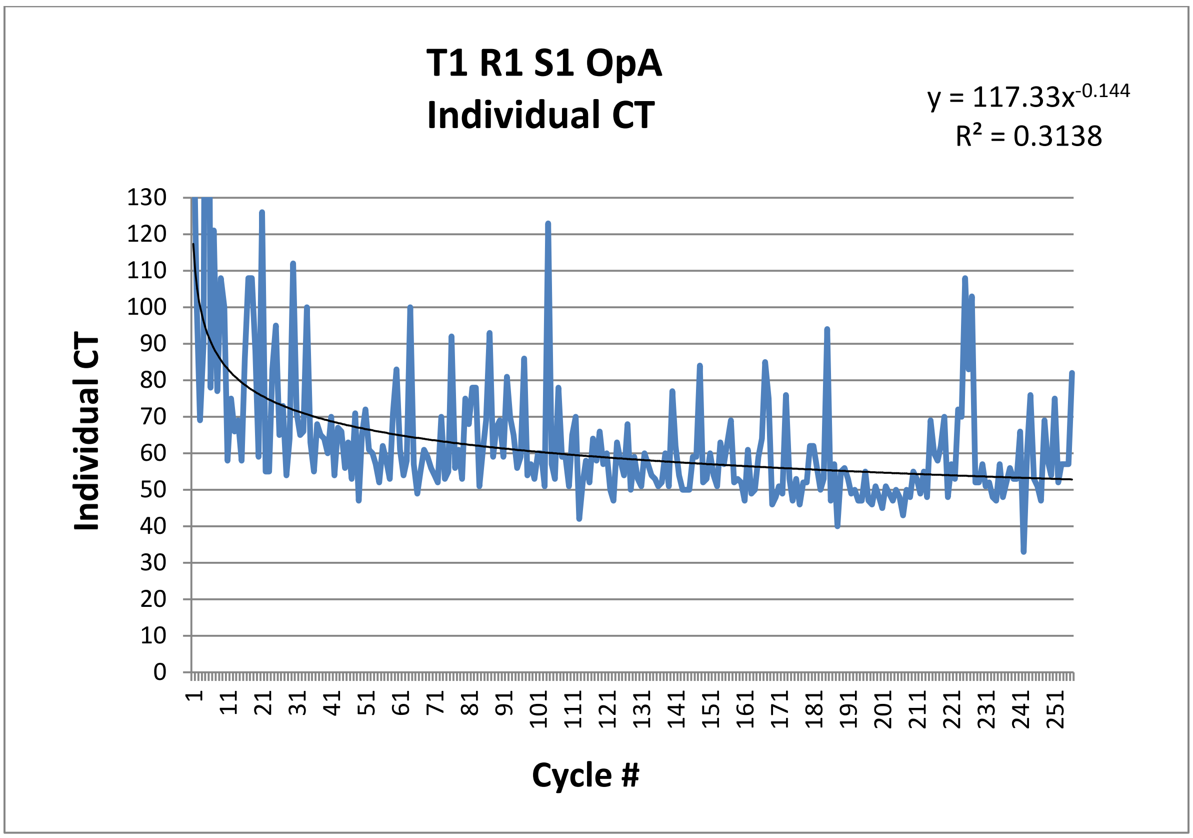

Figure 5.1. Individual single cycle Learning Curve from team 1, Run 1, Operator A, Station 1.

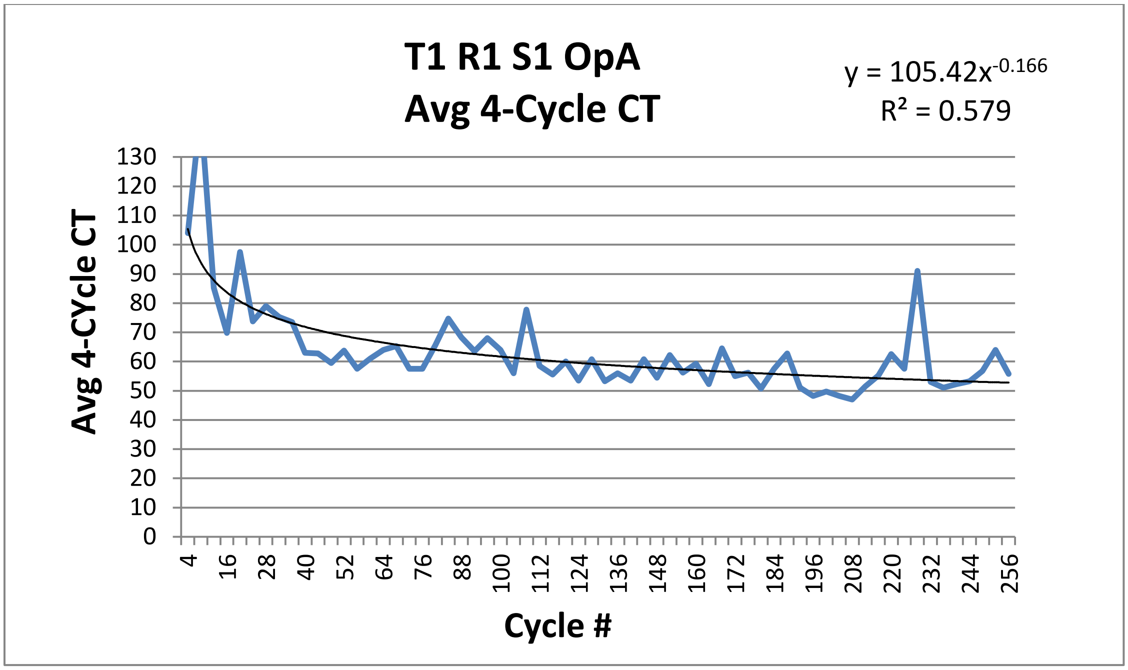

Figure 5.2. Average of 4-Cycle Learning Curve from team 1, Run 1, Operator A, Station 1.

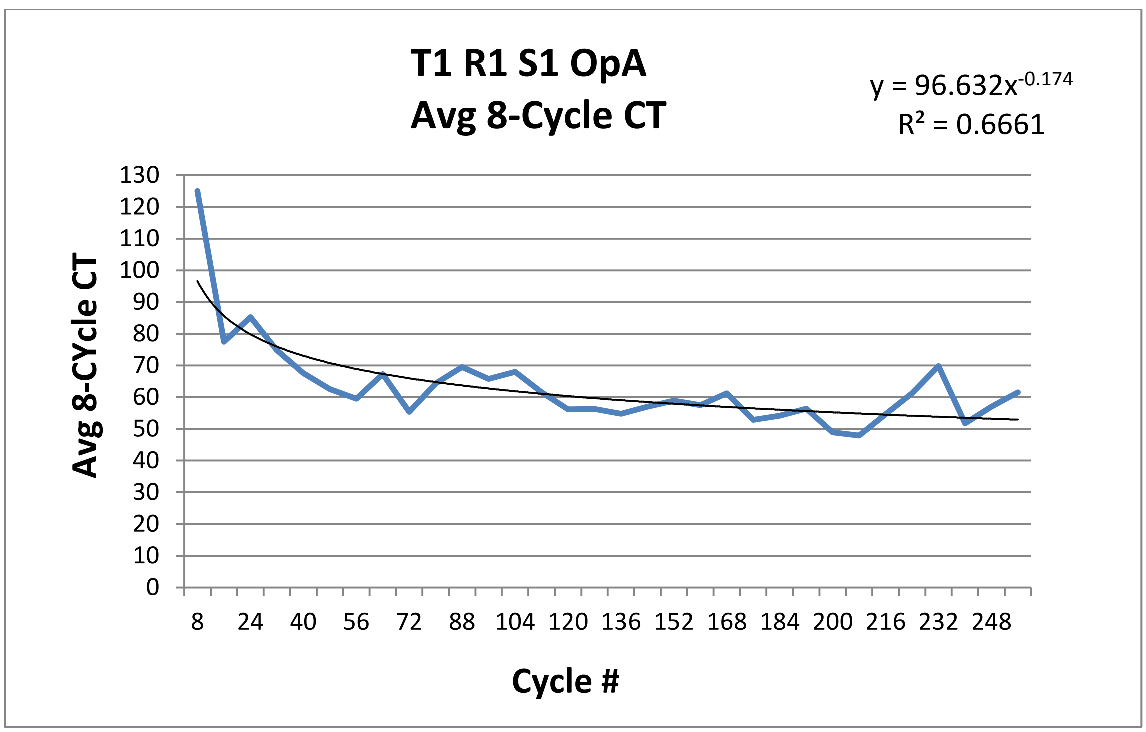

Figure 5.3. Average of 8-Cycle Learning Curve from team 1, Run 1, Operator A, Station 1.

The results of learning curve analysis of the R1 data from each team are presented in Table 5.1 below.

Table 5.1. The Learning Curve Constants (LCC) and Correlation Coefficients (R^2) for individual CT data compared with averaged 4 and 8 CT data sets from R1.

Operator A										
	Team 1		**Team 2**		**Team 3**		**Team 4**		**Range**	
Data Set	**LCC**	**R^2**	**LCC**	**R^2**	**LCC**	**R^2**	**LCC**	**R^2**	**LCC**	**R^2**
1-Cyl	0.144	0.314	0.129	0.262	0.121	0.256	0.104	0.209	0.040	0.105
4-Cyl	0.166	0.579	0.147	0.536	0.127	0.456	0.129	0.507	0.039	0.123
8-Cyl	0.174	**0.666**	0.158	**0.656**	0.133	**0.528**	0.138	**0.583**	0.041	0.138
Operator B										
	Team 1		**Team 2**		**Team 3**		**Team 4**		**Range**	
Data Set	**LCC**	**R^2**	**LCC**	**R^2**	**LCC**	**R^2**	**LCC**	**R^2**	**LCC**	**R^2**
1-Cyl	0.212	0.312	0.274	0.628	0.158	0.289	0.122	0.232	0.167	0.396
4-Cyl	0.227	0.553	0.299	0.779	0.206	0.5906	0.138	0.432	0.161	0.347
8-Cyl	0.236	**0.653**	0.317	**0.895**	0.22	**0.704**	0.151	**0.540**	0.166	0.355

As seen in the table, the results show similar results for each team. While the LCCs are similar, the R^2 value for the single point data is much less than for the averaged data sets, increasing as the number of individual data points averaged increases. As the data is smoothed the fit of the data improves (R^2 increases) while there is little change in the range of the LCC results. As seen in the table, all the 8-cycle sets have an R^2 values greater than %50 accompanied by only slight changes to the LCC values, indicating no loss of data integrity. Data sets with greater than 8 data points were not considered to minimize the loss of visual variation in the data, which is unique to each operator. Due to the higher correlation with minimal change in results LCC values, the 8-cycle set will be the basic data format for the remainder of this study. The complete set of 1 and 8-cycle R1 and R2 LCs with accompanying trendlines, equations and R^2 values are presented in the Appendices A and B.

5.2.2. Graphical Comparison and Tabulated LCC Summaries of Individual Stations and Operators using 256 vs 128 Cycle Learning Curves from R1 and R2

In this section the learning curves (LCs) from R1 and R2 of both groups are examined using 8-cycle set data from both the complete 256-cycle data and the last 128 cycles. Both data sets are examined because each represents a different basis for understanding the treatment results. The 256-cycle data represents a new Start-up or inexperienced operators while the 128-cycle data is obtained after a lot of the knack points or work-a-rounds have been discovered by the operators and they have begun to settle into the routine of the work. The learning curve for new operators is usually much steeper than for more experienced operators. Since the objective of this research is to examine the effects of problem solving thinking, Standardization and waste elimination on experienced operators in relatively Stable processes, the experimental data from the set with the least variability will be used as the baseline. The data and graphs presented in this section are referred to as "individual" learning curves because each Station and operator is examined individually. As previously mentioned, the experimental data is broken into two groups based on whether or not the teams in them received treatment in R3 and R4. During Runs 3 and 4 the operators rotate after cycle 128 and continue in the new Station until the end of cycle 256. Both operators Start each run in the same Station they originally Started in.

Examples of a typical learning curve for the 8-cycle set data from 256 cycles and 128 cycles are presented in Figures 5.4 and 5.5 respectively. The slope of the LC illustrates a major difference between an operator just learning the job and an experienced one. The equation for the line which best fits a power law equation is shown in the top right corner of each figure. As mentioned previously, the exponent of the power equation is the learning curve constant (LCC) which is used in the majority of analysis for this study. The LCCs from each team are presented in Tables 5.2 and 5.3 for the 256 and 128 cycle data respectively. Because in R3 and R4, teams 2 and 3 will comprise the untreated group and teams 1 and 4 the treated grouped, the tables are organized by grouping the results from teams 2 and 3, and teams 1 and 4 together.

The grand average LCC from the data listed in Table 5.2 is -0.194 (Φ = 87%). This corresponds fairly closely to what Dar-El reports as the typical LCC for autonomous learning (Dar-El, 2000). Dar-El has identified a typical autonomous LCC to be -0.152 (Φ = 90%) and a cognitive or induced LCC to be -0.514 (Φ = 70%). Based upon his work, the learning associated with the work designed used in this research appears to represent a typical autonomous learning cycle. The grand average of the 128 cycle LCCs listed in Table 5.3 equals -0.040 which is equivalent to a learning rate of about 97%.

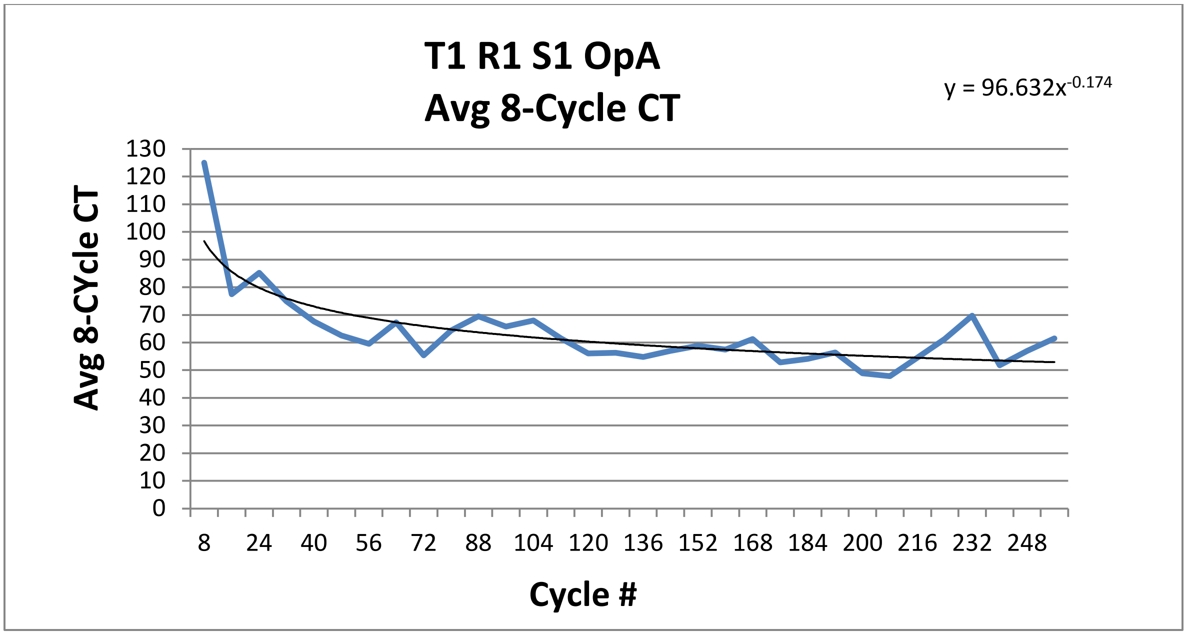

Figure 5.4. Typical 256-cycle LC results for R1 and R2 using 8-cycle data sets.

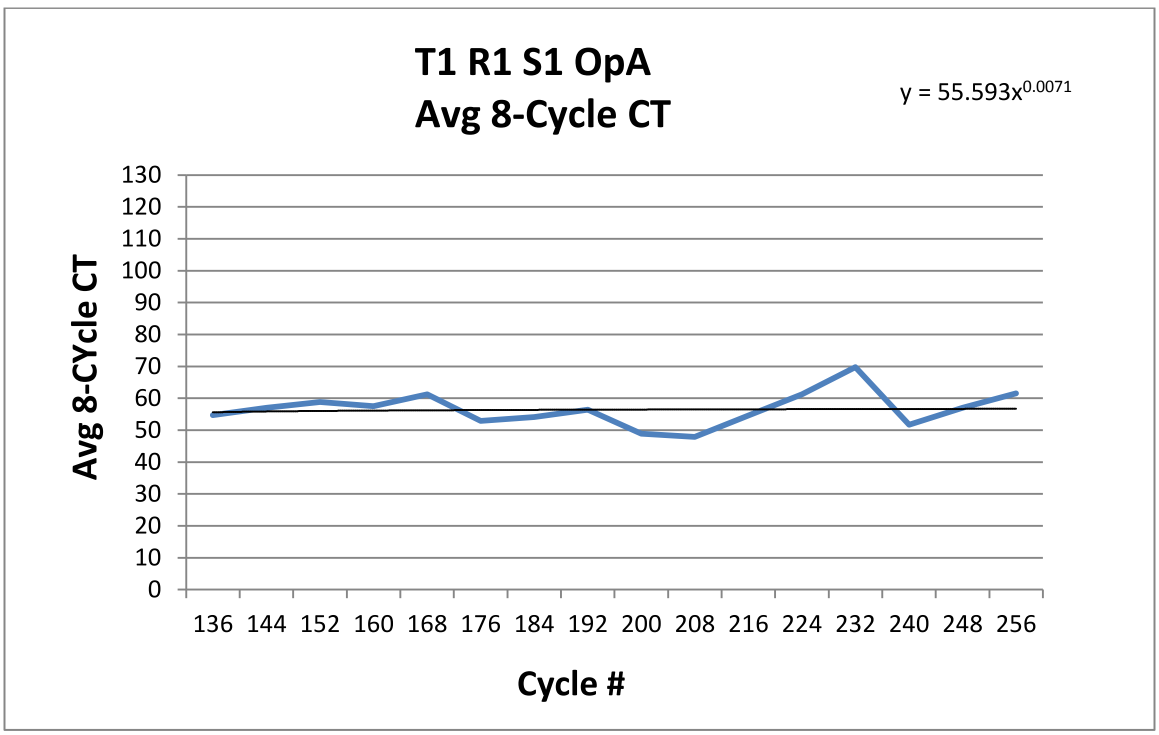

Figure 5.5. Typical Run 128-cycle LC results for R1 and R2 using 8-cycle data sets.

Using the newly defined, more intuitively friendly term of *Demonstrated Learning Rate (Ψ)* which was introduced previously, the results presented in Tables 5.2

and 5.3 can be summarized by Stating the experimentally demonstrated learning rate for R1 and R2 combined is approximately %12 to %13 based on Station to Station and operator to operator respectively for 256 cycle data. Results from the last 128 cycles shown in Tables 5.4 and 5.5 yield a Ψ of 2% to %3 for Station to Station and operator to operator respectively.   The low Ψ value appears consistent with experienced operators experiencing very little autonomous learning, indicating they have created Stable processes as the result of multiple repetitions (>128cycles).

Table 5.2.   Station-Station LCCs obtained using 8-cycle sets from cycles 1-256 of R1 and R2.

Cycle 1- 256 LCC Results by Station					
R1					
T2 & T3 Cycles 1 to 256			T1 & T4 Cycles 1 to 256		
	Station 1 (Operator A)	Station 2 (Operator B)		Station 1 (Operator A)	Station 2 (Operator B)
T2	-0.158	-0.317	T1	-0.174	-0.236
T3	-0.133	-0.220	T4	-0.138	-0.151
Avg	-0.146	-0.269	Avg	-0.156	-0.194
R2					
T2 & T3 Cycles 1 to 256			T1 & T4 Cycles 1 to 256		
	Station1 (Operator B)	Station 2 (Operator A)		Station 1 (Operator B)	Station 2 (Operator A)
T2	-0.109	-0.157	T1	-0.185	-0.465
T3	-0.114	-0.118	T4	-0.121	-0.135
Avg	-0.112	-0.138	Avg	-0.153	-0.300
Total Avg	-0.129	-0.203	Total Avg	-0.155	-0.247
Grand Average by Station = -0.194 => Φ = 87					

Table 5.3. Operator-Operator LCCs obtained using 8-cycle sets from cycles 1-256 of R1 and R2.

Cycle 1- 256 LCC Results by Operator					
R1					
T2 & T3 Cycles 1 to 256			T1 & T4 Cycles 1 to 256		
	Operator A (Station 1)	Operator B (Station 2)		Operator A (Station 1)	Operator B (Station 2)
T2	-0.158	-0.317	T1	-0.174	-0.236
T3	-0.133	-0.220	T4	-0.138	-0.151
Avg	-0.146	-0.269	Avg	-0.156	-0.194
R2					
T2 & T3 Cycles 1 to 256			T1 & T4 Cycles 1 to 256		
	Operator A (Station 2)	Operator B (Station 1)		Operator A (Station 2)	Operator B (Station 1)
T2	-0.157	-0.109	T1	-0.465	-0.185
T3	-0.118	-0.114	T4	-0.135	-0.121
Avg	-0.138	-0.129	Avg	-0.300	-0.155
Total Avg	-0.142	-0.199	Total Avg	-0.228	-0.175
Grand Average by Operator = -0.186 => Φ = 88					

Table 5.4. Station-Station LCCs obtained using 8-cycle sets from cycles 129-256 of R1 and R2.

Cycle 129- 256 LCC Results by Station					
R1					
T2 & T3 Cycles 129 to 256			T1 & T4 Cycles 129 to 256		
	Station 1 (Operator A)	Station 2 (Operator B)		Station 1 (Operator A)	Station 2 (Operator B)
T2	-0.006	-0.017	T1	0.0071	0.0047
T3	-0.078	-0.125	T4	-0.039	-0.024
Avg	-0.042	-0.071	Avg	-0.016	-0.010
R2					
T2 & T3 Cycles 129 to 256			T1 & T4 Cycles 129 to 256		
	Station 1 (Operator B)	Station 2 (Operator A)		Station 1 (Operator B)	Station 2 (Operator A)
T2	-0.045	-0.009	T1	-0.106	-0.07
T3	-0.032	-0.016	T4	-0.025	-0.056
Avg	-0.039	-0.013	Avg	-0.066	-0.032
Total Avg	-0.041	-0.042	Total Avg	-0.041	-0.021
Grand Average by Station = -0.036 => Φ = 98					

Table 5.5. Operator-Operator LCCs obtained using 8-cycle sets from cycles 129-256 of R1 and R2.

Cycle 129- 256 LCC Results by Operator					
R1					
T2 & T3 Cycles 129 to 256			T1 & T4 Cycles 129 to 256		
	Operator A (Station 1)	Operator B (Station 2)		Operator A (Station 1)	Operator B (Station 2)
T2	-0.006	-0.017	T1	0.0071	0.0047
T3	-0.078	-0.125	T4	-0.039	-0.024
Avg	-0.042	-0.071	Avg	-0.016	-0.010
R2					
T2 & T3 Cycles 129 to 256			T1 & T4 Cycles 129 to 256		
	Operator A (Station 2)	Operator B (Station 1)		Operator A (Station 2)	Operator B (Station 1)
T2	-0.009	-0.045	T1	-0.07	-0.106
T3	-0.016	-0.032	T4	-0.056	-0.025
Avg	-0.013	-0.041	Avg	-0.032	-0.066
Total Avg	-0.028	-0.056	Total Avg	-0.024	-0.038
Grand Average by Operator = -0.040 => Φ = 97					

The results shown in Tables 5.2 through 5.5 are illustrated graphically in Figures 5.6 and 5.7. The combined 256 and 128-cycle Station-specific LCC data is shown in Figure 5.6 and the operator-specific data is shown in Figure 5.7. In order to determine the effects of treatments on R3 and R4 results it is important that R1 and R2 represent a Stable baseline condition. This will be evaluated statistical in the next section.

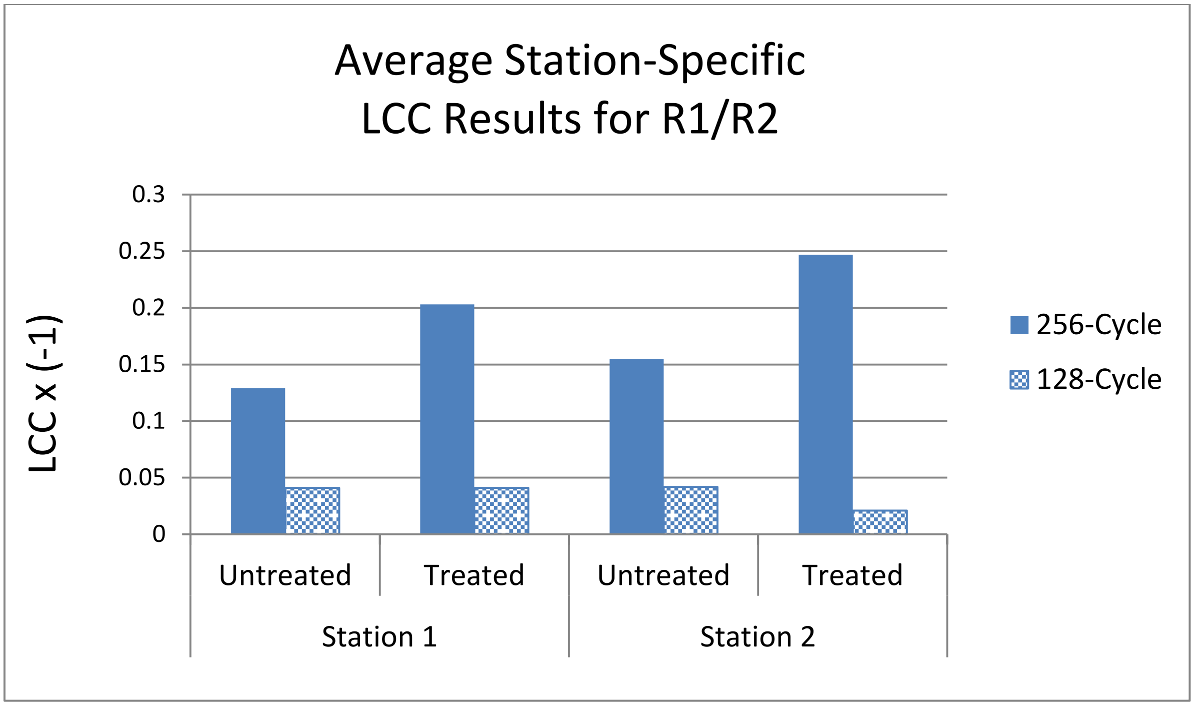

Figure 5.6. Station- specific LCC results from R1 and R2.

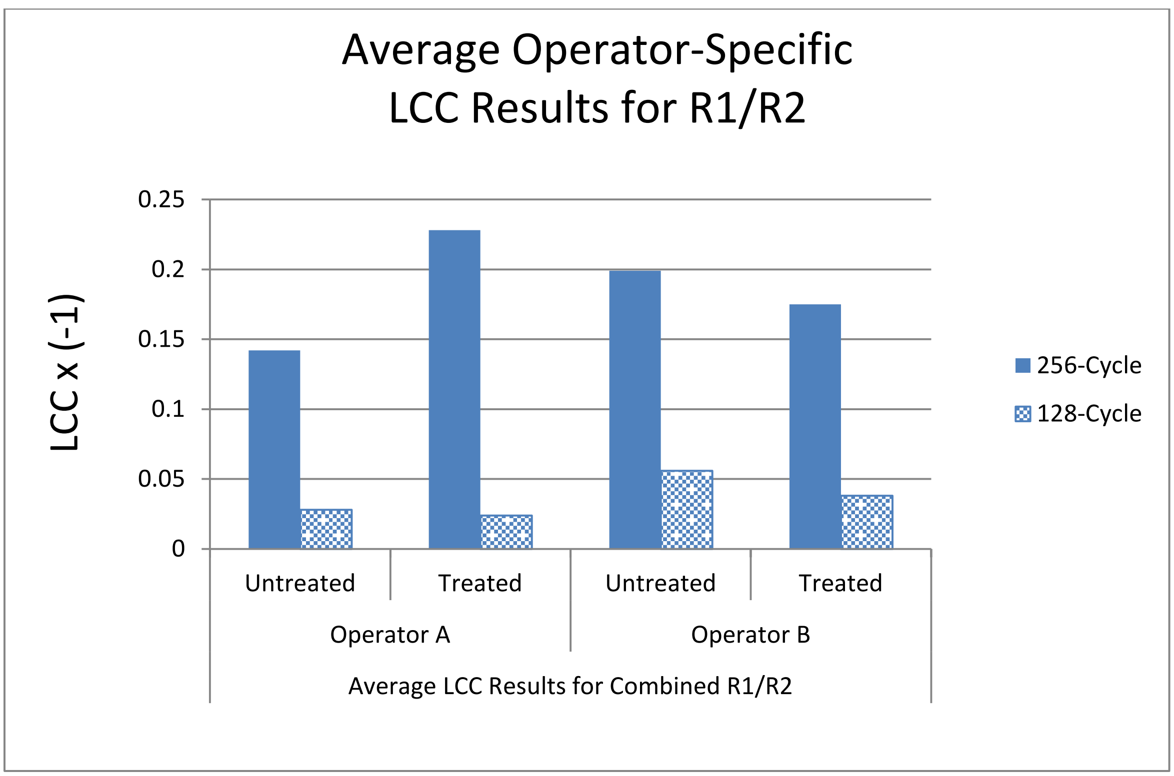

Figure 5.7. Operator-specific LLC results from R1 and R2.

5.2.3. Two-Sample t-test analysis of R1 and R2 256-Cycle versus 128-Cycle LCC Data Sets (Station-Specific Statistical Analysis)

The LCCs obtained from each group tabulated in Tables 5.2 through 5.5 are compared using a statistical method called the Two-Sample t-Test Assuming Equal Variances to determine the uniqueness of the means of the data set from each group. In this test, the teams are grouped according to their future treatment groups. In this analysis the data from teams 2 and 3 are compared with data from teams 1 and 4 since these groups represent the untreated and treated groups respectively. Under ideal conditions, the results of the t-test should indicate the two data sets represent the same populations. Although only the 128-cycle data sets will be used for comparison with R3 and R4 results, the 256-cycle data is also examined statistical as a further indication of experimental consistency. If no bias exists in the LCC results of the two groups, the statistical analysis will result in t-Stat values less than a corresponding calculated t-critical value, indicating the means of the two data sets are equivalent.

The results of the t-test analysis using Station- specific and operator-specific data sets are presented in Appendices C and D respectively. The Station-specific data compares the LCC results from a single Station for R1 and R2 combined. As a result, the data included LCC results from both Operator A and Operator B. Similarly, the operator-specific data contains LCC data from both Station 1 and 2. As mentioned above, the expected outcomes for non-biased results would be to have no statistical difference between the groups. In addition, the least amount of variance within the data sets is also preferred. The results of the statistical tests are summarized in Table 5.6. From the results presented in Table 5.6, it is clear both the 256 and 128 cycle LCC data results statistically represent the same populations. In all four conditions listed, the t-Stat values are less than their corresponding t-critical values. In addition, the p values are much greater than 0.05 which represents the level of certainty the t-test results are valid (p = 0.05 indicates there is a 5% probability the data is from the same sample population, or a %95 probability it's from different data sets).

Table 5.6. Summary Data of 256-cycle and 128-cycle Two-Sample t-test results from Station 1 and Station 2.

256-Cycle LCC Data			128-Cycle LCC Data		
teams 2 & 3 vs teams 1 & 4			teams 2 & 3 vs teams 1 & 4		
	Station 1	Station 2		Station 1	Station 2
Observations	4	4	Observations	4	4
T-Stat	1.392	0.499	T-Stat	0.017	-0.167
T-Critical (2-tail)	2.45	2.45	T-Critical (2-tail)	2.45	2.45
P-value (2-tailed)	0.213	0.635	P-value (2-tailed)	0.987	0.873

Table 5.7. Summary Data of 256-cycle and 128-cycle Two-Sample t-test results from Operator A and Operator B.

256-Cycle LCC Data			128-Cycle LCC Data		
teams 2 & 3 vs teams 1 & 4			teams 2 & 3 vs teams 1 & 4		
	Operator A	Operator B		Operator A	Operator B
Observations	4	4	Observations	4	4
T-Stat	1.080	-0.303	T-Stat	0.511	-0.507
T-Critical (2-tail)	2.45	2.45	T-Critical (2-tail)	2.45	2.45
P-value (2-tailed)	0.322	0.772	P-value (2-tailed)	0.627	0.630

In the present analysis, the p-value ranges from 0.213 to 0.635 for the 256-cycle data and from 0.873 to 0.987 for the 128 cycle data. For the 256-cycle data sets the results indicate there are a 21% chance the Station 1 results from teams 2 and 3, and teams 1 and 4 are from the same population and a 64% chance the Station 2 data sets are the same. Similarly, for the 128-cycle data sets there is a 99% chance the Station 1 data sets are the same and an 87% chance the Station 2 data sets are also the same. Based on these t-test results the 128-cycle data sets appear to be more consistent with each other, providing a common baseline for subsequent analysis.

5.2.4. Operator -Specific Statistical Analysis

The statistical results using operator specific data are presented in Appendix D. Similar to the Station specific case, the operator specific case means that LCC results for each operator will include data from both Stations. Table 5.7 contains the combined t-Stat, t-critical and p-value statistical results for the operator specific analysis. From the summarized data in Table 5.7, all four t-Stat values are less than their corresponding t-critical values, indicating there is no difference in the LCC data sets used in the analysis. According to the p-values, the probability the LCC data used in the analysis are from the same sample populations range from 32% for Operator A and 77% for Operator B using 256-cycle LCC data and 63% for both Operator A to 37% and Operator B using 128-cycle LCC data. These results are very similar to the Station-specific results seen above.

Considering the t-test results from the R1 and R2 LCC data from both a Station specific and operator specific perspectives, all sample sets analyzed are statistical ly from the same populations. This means there is no statistical difference between the results from teams 2 and 3 and teams 1 and 4. The results further indicate the 128-cycle LCC data sets are more internally consistent than their 256-cycle counterparts.

5.2.5. The Variance of 256 and 128-Cycle Data Sets

To further explore the differences between the 256 and 128-cycle data sets another set of statistical tests were performed. The variance of each data set is an indication of the within sample consistency or the variability of the sample set. Variance is the square of the sample Standard deviation and therefore measures the dispersion or spread of the sample data. In this case that relates directly to the variation of learning occurring between the same operators and Stations of the four teams. The variance was obtained by comparing the 256 and 128-cycle data using the Paired t-Test from both Station-specific and operator-specific data sets. Since it has been determined there is no difference between the treated and untreated teams LCC results for R1 and R2, data sets from the same cycle sets (either 256 or 128) were paired according to Station and operator-specific conditions. The results of the analysis are summarized in Table 5.8 and graphically illustrated in Figure 5.8 for both the Station-specific and operator-specific data sets. The complete results of the t-test analysis are presented in Appendix E.

Table 5.8. Within-sample variances determined from Paired t-test of 256 versus 128-cycle data sets.

Variance of R1 and R2 Combined			
Station 1		Station 2	
256-Cycle	128-Cycle	256-Cycle	128-Cycle
0.0008	0.0014	0.0137	0.0018
Operator A		Operator B	
256-Cycle	128-Cycle	256-Cycle	128-Cycle
0.0015	0.0010	0.0053	0.0020

Figure 5.8 clearly illustrates the within sample variation of the 256-cycle data is significantly greater than its corresponding 128-cycle data. In particular it shows the

difference between the LCC distributions of the 256-cycle data are much more pronounced than those of the 128-cycle data sets. It also shows the Station to Station and operator to operator differences are more pronounced using the 256-cycle data sets. This result illustrates how it is possible for the distribution of learning within organizations to be non-uniform, even in within the same areas of an organization, producing the same item.

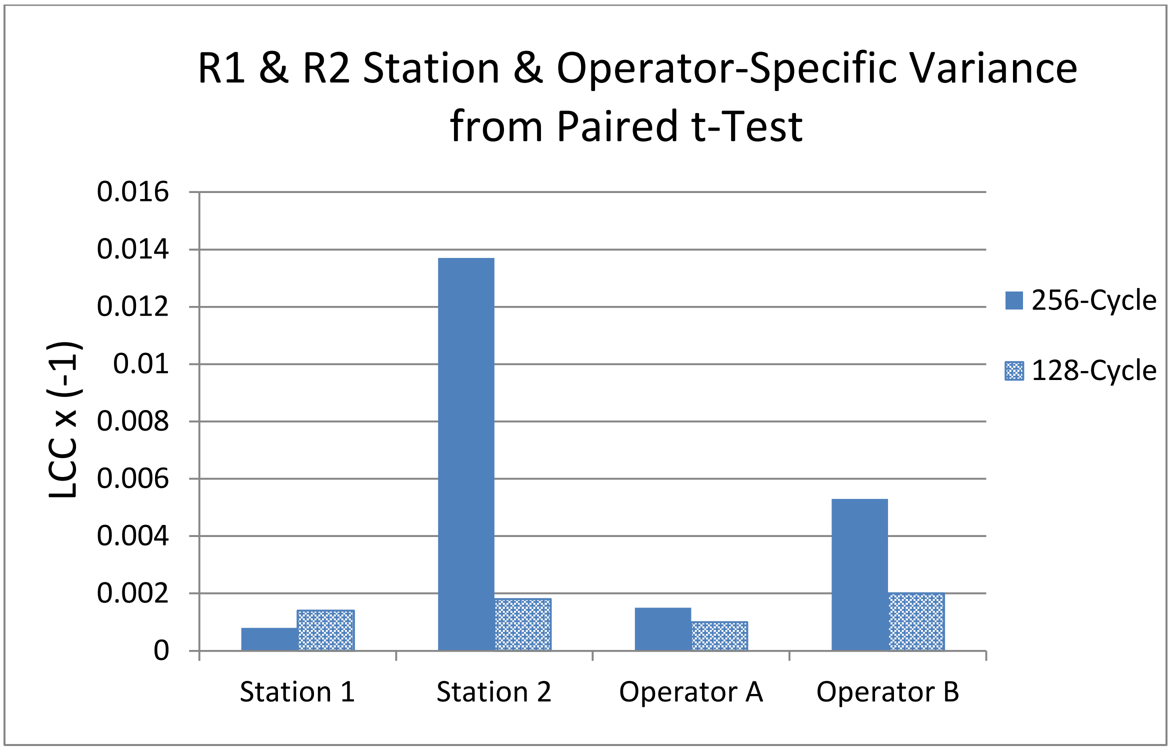

Figure 5.8. Station and Operator-specific Variance shown in Table 5.8 calculated from Paired t-test using R1 & R2 data sets.

5.3. The Results of Individual Learning Curve Analysis of R3 and R4

5.3.1. Determining teams for Treated and Untreated Groups

In this section the method for pairing teams for treatment are presented. Once R1 and R2 were completed, the LCC obtained from the combined R1 and R2 throughput time (TPT) was determined using the 256 cycle 8-set cycle data to rank the teams before R3 and R4 began. Table 5.9 shows the results of the TPT analysis and the rank assigned to each team based on their performance. Based on the average TPT LCC results, the teams were ranked and grouped to give the closest equal total average TPT LCC value for the resultant group. Using this method, teams 1 and 4, and teams 2 and 3 were grouped. For scheduling purposes, teams 2 and 3 were chosen to be the untreated group and completed R3 and R4 first. The remaining teams (1 and 4) conducted their treated runs last.

Table 5.9. LCC based on total throughput time (TPT) from 256-cycle R1 and R2 data combined.

	R1 + R2			
	TPT (S1+S2)		Avg TPT	Rank
	R1	R2		
T1	0.204	0.29	0.247	1
T2	0.224	0.131	0.1775	2
T3	0.18	0.116	0.148	3
T4	0.144	0.127	0.1355	4

5.3.2. R3 and R4 Individual Learning Curves Results

The term “individual” learning curves is used in this study to distinguish between LCs created using data derived directly from only one source such as Station 1 or operator A. It may also refer to more specific data such as Station 1, operator A since during the course of the experiments operators A and B worked at both Station and 2. The same applies to references to Station 1 or Station 2.

Typical learning curves for R3 and R4 are presented in Figures 5.9 and 5.10 respectively. Compared to the full cycle (256 cycles) R1 and R2 learning curves (Figure 5.3), the full R3 and R4 LCs are only 128 total cycles, which is the result of a job rotation at cycle 129. The slope of the full R3 and R4 LCs are much less pronounced than their full cycle R1/R2 counterparts. The overall shape differences between the full R1/R2 and R3/R4 LCs are an indication of the experience level of the operators. As a reminder, each operator produced 256 units in both Stations during R1 and R2, making them experienced operators before the onset of R3 and R4. However, as mentioned previously, only the last 128 cycles of the full 256-cycle data sets were used in the analysis to provide an "experienced" operator baseline in R1/R2 for comparison purposes with R3 and R4 results. Figures 5.9 and 5.10 are examples of the learning curves from an untreated team in (team 3) R1/R2 and R3/R4. The LCs shown these figures illustrate how the LCs are used to determine the amount of learning experienced by each operator during the course of the experiments. As mentioned previously, LCs from R1 and R2 represents the baseline condition for both treated and untreated teams. The difference in the LCCs obtained from the trendline and power equation shown in Figures 5.9 and 5.10 are the learning curve coefficients (LCCs), which directly relate to learning rate using Equation 2.1 and Equation 2.2 (pg 38). The difference between the R1/R2 and subsequent R3 and R4 LCC results are the basis for the learning curve analysis performed for this study. Inspection of Figures 5.9 and 5.10 shows that both the 128-cycle R12/R2 and R3 represent comparable learning conditions for team 3. Figures 5.11 and 5.12 are examples of the same conditions for a treated team (team 4). Notice the difference in the slope of the trendline, the increased LCC and the ultimate CT obtained. A comparison of the team 3 and team 4 results show the effects of Standardization / systematic problem solving on the LCC of team 4.

As part of their instruction for R3 and R4, each operator was asked to perform the first 16 cycles without making changes as indicated by the solid line at the 16-cycle point in both, Figures 5.9 and 5.11.   This was intended to allow operators to settle in after their 5 to 7 day layoffs before applying treatments. Even though R3 and R4 were performed on consecutive days, the same rule applied to R4. An analysis of the difference in the first 16 cycles between R3 and R4 for treated and untreated teams may also give an indication of the effects of using Standard work as a Starting point for performing work compared to the individually oriented, informal training which occurred in the untreated teams. The difference between the 128 and 112-cycle data is statistical ly analyzed in the following section to get some indication of how eliminating the first 16 cycles impacts the LCC results.

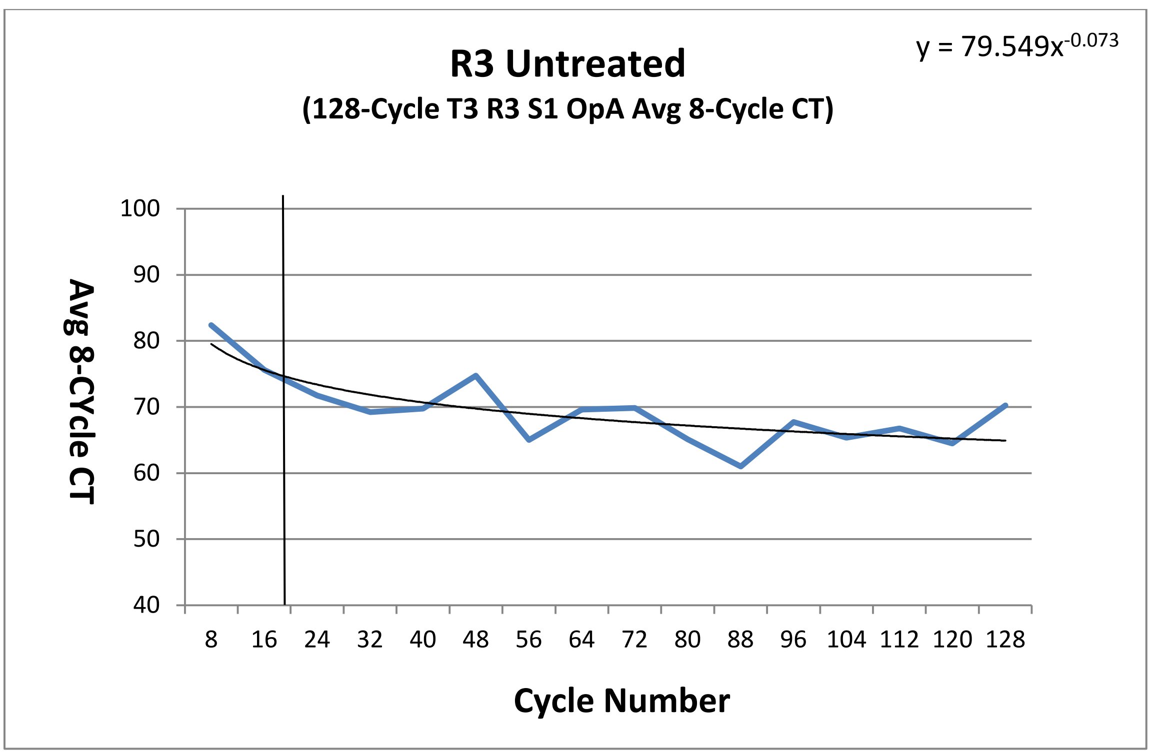

Figure 5.9.   Untreated 128-Cycle Individual Learning Curve from team 3, Station 1, Operator A for R3.

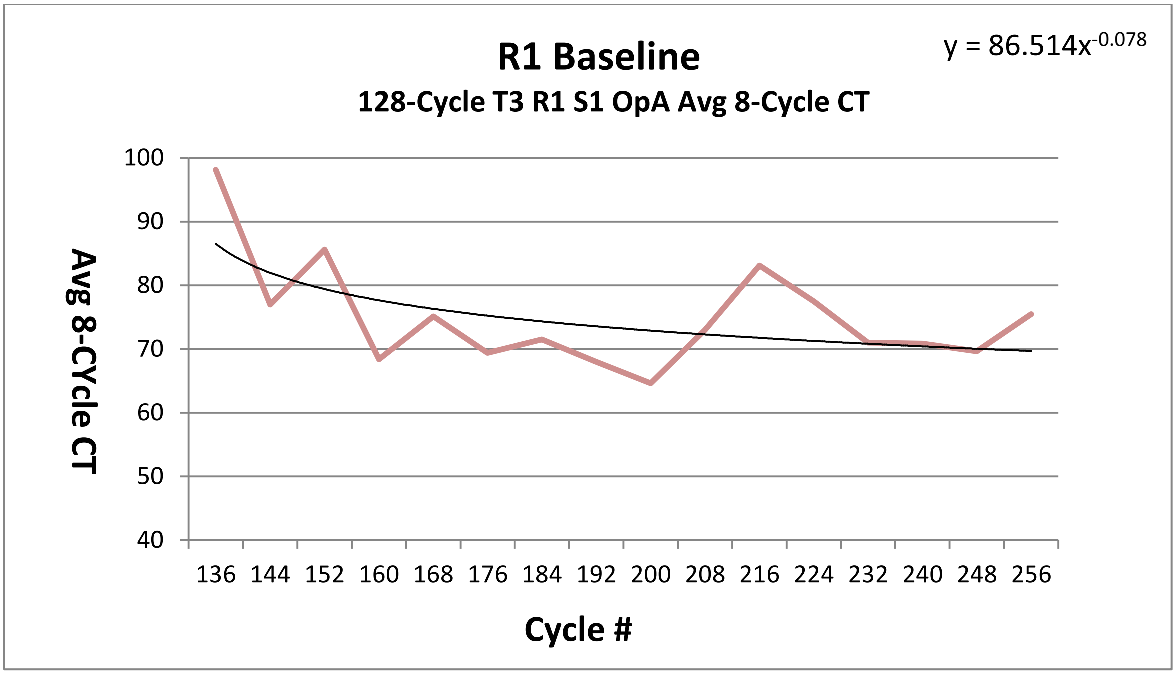

Figure 5.10. Last 128 Cycles of the 256-Cycle Individual Learning Curve from team 3, Station 1, Operator A for R1.

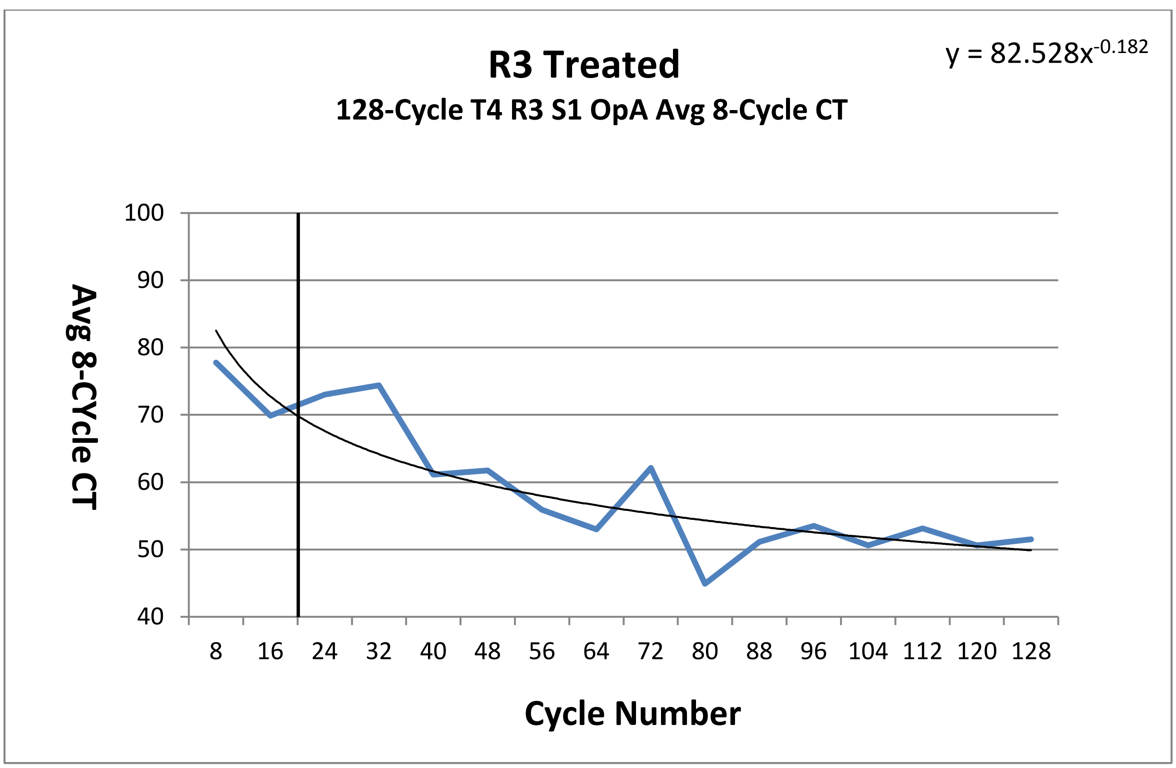

Figure 5.11. Treated 128-Cycle Individual Learning Curve from team 4, Station 1, Operator A for R3.

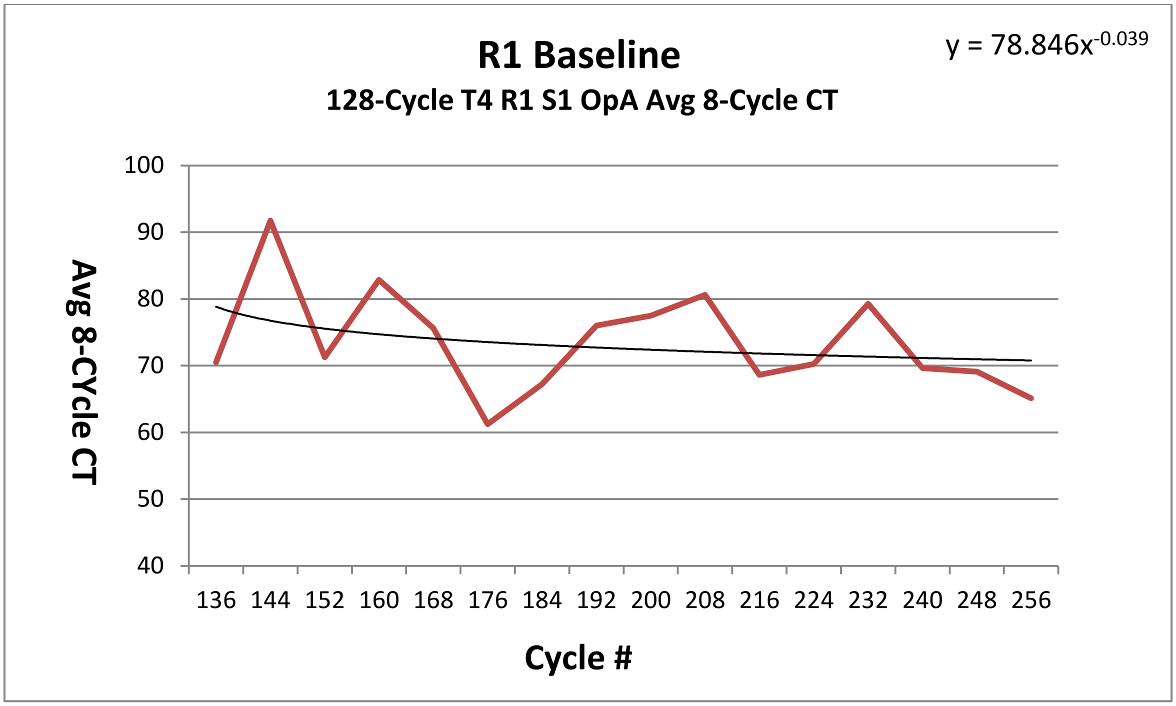

Figure 5.12. Last 128 Cycles of the 256-Cycle Individual Learning Curve from team 3, Station 1, Operator A for R1.

The LCC analysis will use 112-cycle data in R3 and R4. Complete sets of all R3 and R4 LCs can be seen in Appendices F and G for R3 and R4 respectively

5.3.3. Comparative Analysis of 128 and 112-Cycle LCC Results

Tables 5.10 and 5.11 contain the complete set of LCCs obtained using the 128 and 112 cycle data for Station and operator-specific perspectives respectively. The results of statistical analysis of the 128 versus 112 cycle LLC data are presented in Table 5.12. The table summarizes the results of paired t-test analysis and includes the variance, t-Stat, t-critical and p-value data. From the data in Table 5.12, the p-value for the R3 Operator A and Station 2 data sets indicate they are significantly different (at 90% level) from each other. In particular, for Operator A there is only a 5% probability the 128-cycle and 112-cycle data sets are the same and for the Station 2 data sets, there is only an 8%

probability they are the same. All the remaining data sets are statistical ly similar to each other.

Table 5.10. Station-specific results of LC analysis using 128 and 112 cycle data sets for R3 and R4.

Individual Learning Curve Coefficients (LCC)								
	R3				R4			
	128-Cycle		112-Cycle		128-Cycle		112-Cycle	
	Station 1	Station 2	Station 1	Station 2	Station 1	Station 2	Station 1	Station 2
team 2								
Operator A	-0.054	-0.061	-0.038	-0.08	-0.049	0.027	-0.038	0.099
Operator B	-0.062	-0.161	-0.076	-0.122	-0.019	-0.093	0.015	-0.053
team 3								
Operator A	-0.073	-0.105	-0.034	-0.077	-0.084	-0.014	-0.094	-0.048
Operator B	-0.105	-0.081	-0.075	-0.056	0.006	-0.075	-0.016	-0.085
Total Untreated Average	-0.074	-0.102	-0.056	-0.084	-0.037	-0.038	-0.033	-0.022
team 1								
Operator A	-0.116	-0.101	-0.122	-0.076	-0.027	-0.098	-0.019	-0.123
Operator B	-0.052	-0.146	-0.078	-0.163	-0.105	0.033	-0.082	-0.01
team 4								
Operator A	-0.182	-0.115	-0.159	-0.097	-0.095	-0.098	-0.026	-0.049
Operator B	-0.063	-0.148	-0.087	-0.076	-0.037	0.007	-0.049	-0.09
Total Treated Average	-0.103	-0.128	-0.112	-0.104	-0.066	-0.039	-0.044	-0.068

Although eliminating the first 16 cycles of data has a significant impact on two conditions, it should have a stabilizing effect on the resultant learning curve or at least give each operator a chance to re-acquaint themselves with the work.

Table 5.11. Operator-specific results of LC analysis using 128 and 112 cycle data sets for R3 and R4.

Individual Learning Curve Coefficients (LCC)								
	R3				R4			
	128-Cycle		112-Cycle		128-Cycle		112-Cycle	
	Operator A	Operator B	Operator A	Operator B	Operator A	Operator B	Operator A	Operator B
team 2								
Station 1	-0.054	-0.062	-0.038	-0.076	-0.049	-0.019	-0.038	0.015
Station 2	-0.061	-0.161	-0.08	-0.122	0.027	-0.093	0.099	-0.053
team 3								
Station 1	-0.073	-0.105	-0.034	-0.075	-0.084	0.006	-0.094	-0.016
Station 2	-0.105	-0.081	-0.077	-0.056	-0.014	-0.075	-0.048	-0.085
Total Untreated Average	-0.073	-0.102	-0.057	-0.082	-0.030	-0.045	-0.020	-0.035
team 1								
Station 1	-0.116	-0.052	-0.122	-0.078	-0.027	-0.105	-0.019	-0.082
Station 2	-0.101	-0.146	-0.076	-0.163	-0.098	0.033	-0.123	-0.01
team 4								
Station 1	-0.182	-0.083	-0.159	-0.087	-0.095	-0.037	-0/026	-0.049
Station 2	-0.115	-0.148	-0.097	-0.076	-0.098	0.007	-0.049	-0.09
Total Treated Average	-0.129	-0.107	-0.114	-0.101	-0.080	-0.026	-0.-054	-0.058

Table 5.12. Results of paired t-test analysis of 128 vs 112-cyle LLC data from R3 and R4.

Summary of Paired t-Test results from Individual 128 vs 112-Cycle R3 and R4 LCC Results					
R3					
	Station 1			Operator A	
	128-Cycles	112-Cycles		128-Cycles	112-Cycles
Variance	0.00198	0.00170	Variance	0.001656	0.00171
T-Stat	-0.529		T-Stat	-2.31336	
T-Critical (2-tail)	2.365		T-Critical (2-tail)	2.365	
P-value (2-tailed)	0.613		P-value (2-tailed)	**0.054**	
	Station 2			Operator B	
	128-Cycles	112-Cycles		128-Cycles	112-Cycles
Variance	0.00122	0.00116	Variance	0.001769	0.00118
T-Stat	-2.055		T-Stat	-1.096	
T-Critical (2-tail)	2.365		T-Critical (2-tail)	2.365	
P-value (2-tailed)	**0.079**		P-value (2-tailed)	0.303	
R4					
	Station 1			Operator A	
	128-Cycles	112-Cycles		128-Cycles	112-Cycles
Variance	0.00157	0.00128	Variance	0.002195	0.004265
T-Stat	-1.211		T-Stat	-1.197	
T-Critical (2-tail)	2.365		T-Critical (2-tail)	2.365	
P-value (2-tailed)	0.265		P-value (2-tailed)	0.270	
	Station 2			Operator B	
	128-Cycles	112-Cycles		128-Cycles	112-Cycles
Variance	0.00335	0.00454	Variance	0.001769	0.00118
T-Stat	0.302		T-Stat	-1.096	
T-Critical (2-tail)	2.365		T-Critical (2-tail)	2.365	
P-value (2-tailed)	0.771		P-value (2-tailed)	0.309	

5.3.4. Combined Individual 128-Cycle R1/R2 and 112-Cycle R3/R4 LCC Results

The combined LCC results from R1, R2, R3 and R4 obtained using the individual experimentally derived learning curves are presented in Tables 5.13 and 5.14 from the operator and Station-specific perspectives respectively. All the LCC data from this point on consists of 128-cycle data for R1 and R2, and 112-cycle data for R3 and R3. The average results shown in the tables are illustrated in Figures 5.13 and 5.14. Two common trends stand out in the figures. The first is that the average LCC results for the treated teams were greater than their untreated counterparts. Secondly, the change in LCC from R3 to R4 was less pronounced for the treated teams than the untreated ones. To determine whether these differences are statistical ly significant Two-Sided t-Tests were performed on the data in Tables 5.13 and 5.14. The analysis was confined to the R3 and R4 data sets because the R1/R2 data was previously found to represent a good baseline. The R1/R2 results were presented in Part I and the t-test results are presented in Appendices C, D and E. The complete results of the R3 and R4 statistical analysis for this section are presented in Appendices I through L. The results of the statistical analysis summarized in Table 5.15 and show the treatments had a significant (> 95% probability) effect on R3 Station 1 and R3 Operator A according to the p-values. This result is consistent with what is shown graphically in Figures 5.13 and 5.14, which shows that the greatest difference in treated versus untreated LCC results occurs in those conditions in R3. Another two-sided t-test was performed on the combined data (Station 1+2 and Operator A + B) from Tables 5.13 and 5.14. The total averages for the Station and operator-specific data sets are shown in Table 5.16 and graphically presented in Figure 5.15.

Table 5.13. Operator-specific individual LCC results from R1 through R4.

Operator-Specific Individual Learning Curve Coefficients (LCC)						
	R1/R2		R3		R4	
	Operator A	Operator B	Operat or A	Operator B	Operat or A	Operato r B
team 2						
Station 1	-0.006	-0.045	-0.038	-0.076	-0.038	0.015
Station 2	-0.009	-0.017	-0.08	-0.122	0.099	-0.053
team 3						
Station 1	-0.078	-0.032	-0.034	-0.075	-0.094	-0.016
Station 2	-0.016	-0.125	-0.077	-0.056	-0.048	-0.085
Total Avg Untreated	**-0.027**	**-0.055**	**-0.057**	**-0.082**	**-0.020**	**-0.035**
team 1						
Station 1	0.0071	-0.106	-0.122	-0.078	-0.019	-0.082
Station 2	-0.07	0.0047	-0.076	-0.163	-0.123	-0.01
team 4						
Station 1	-0.039	-0.066	-0.159	-0.087	-0/026	-0.049
Station 2	-0.056	-0.024	-0.097	-0.076	-0.049	-0.09
Total Avg Treated	**-0.039**	**-0.048**	**-0.114**	**-0.101**	**-0.-054**	**-0.058**

Table 5.14. Station-specific individual LCC results from R1 through R4.

Station-Specific Individual Learning Curve Coefficients (LCC)						
	R1/R2		R3		R4	
	Station 1	Station 2	Station 1	Station 2	Station 1	Station 2
team 2						
Operator A	-0.006	-0.009	-0.038	-0.08	-0.038	0.099
Operator B	-0.045	-0.017	-0.076	-0.122	0.015	-0.053
team 3						
Operator A	-0.078	-0.016	-0.034	-0.077	-0.094	-0.048
Operator B	-0.032	-0.125	-0.075	-0.056	-0.016	-0.085
Total Avg Untreated	**-0.040**	**-0.042**	**-0.056**	**-0.084**	**-0.033**	**-0.022**
team 1						
Operator A	0.0071	-0.07	-0.122	-0.076	-0.019	-0.123
Operator B	-0.106	0.0047	-0.078	-0.163	-0.082	-0.01
team 4						
Operator A	-0.039	-0.056	-0.159	-0.097	-0.026	-0.049
Operator B	-0.066	-0.024	-0.087	-0.076	-0.049	-0.09
Total Avg Treated	**-0.053**	**-0.036**	**-0.112**	**-0.104**	**-0.044**	**-0.068**

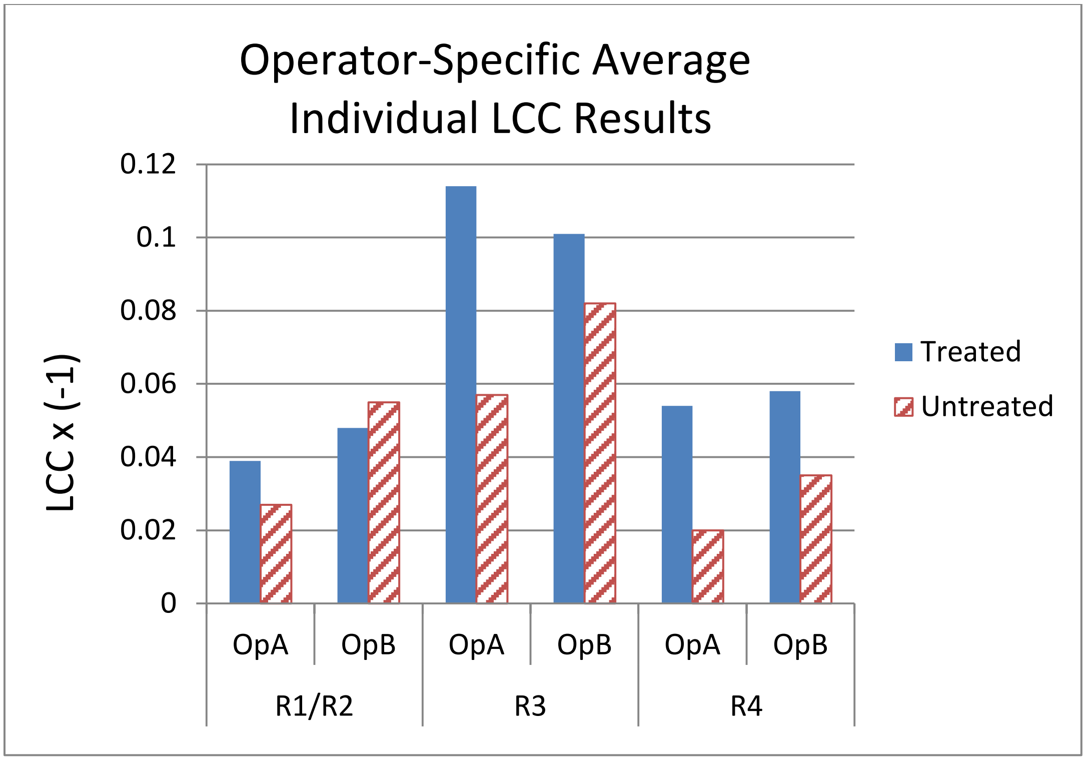

Figure 5.13. Operator-specific individual LCC results from R1 through R4.

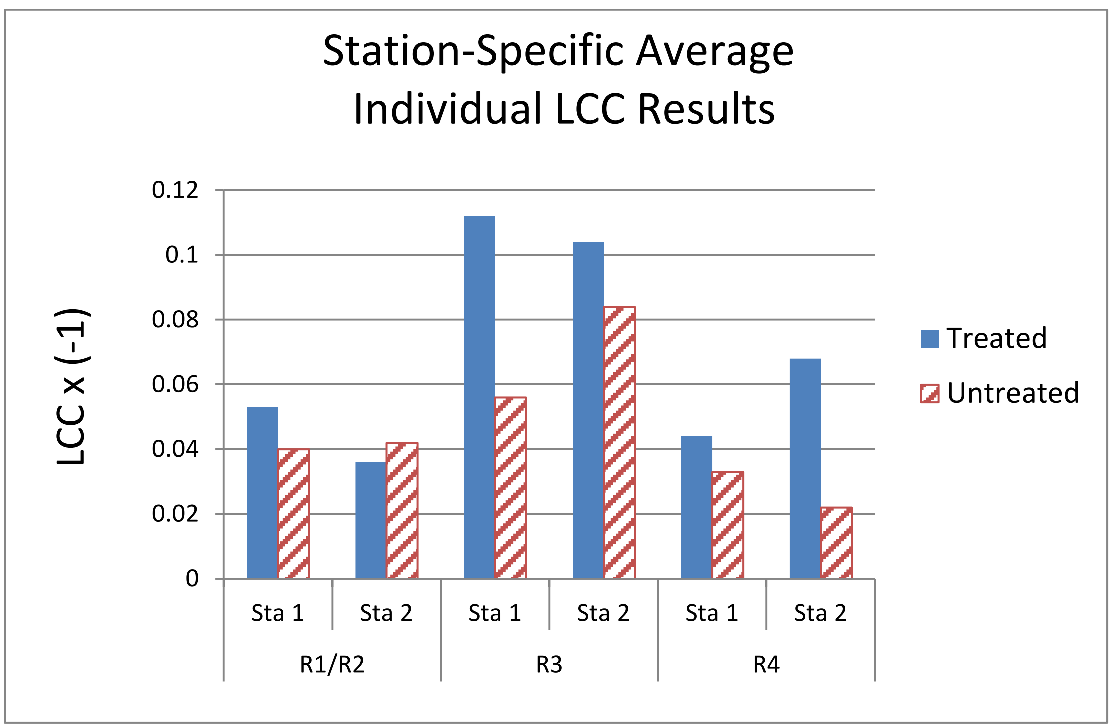

Figure 5.14. Station-specific individual LCC results from R1 through R4.

Table 5.15. Two-Sample t-test results comparing untreated and treated teams using R3 and R4 Individual LCC results.

Summary of Two-Sample t-Test results from Individual Untreated versus Treated R3 and R4 LCC Results					
R3					
	Station 1			Operator A	
	Untreated	Treated		Untreated	Treated
Variance	0.0005	0.0014	Variance	0.0006	0.0013
Observations	4		Observations	4	
T-Stat	2.567		T-Stat	2.595	
T-Critical (2-tail)	2.45		T-Critical (2-tail)	2.45	
P-value (2-tailed)	**0.042**		P-value (2-tailed)	**0.040**	
	Station 2			Operator B	
	Untreated	Treated		Untreated	Treated
Variance	0.0008	0.0017	Variance	0.0008	0.0017
Observations	4		Observations	4	
T-Stat	0.776		T-Stat	0.747	
T-Critical (2-tail)	2.45		T-Critical (2-tail)	2.45	
P-value (2-tailed)	0.467		P-value (2-tailed)	0.483	
R4					
	Station 1			Operator A	
	Untreated	Treated		Untreated	Treated
Variance	0.0021	0.0008	Variance	0.0069	0.0023
Observations	4		Observations	4	
T-Stat	0.398		T-Stat	0.710	
T-Critical (2-tail)	2.45		T-Critical (2-tail)	2.45	
P-value (2-tailed)	0.704		P-value (2-tailed)	0.505	
	Station 2			Operator B	
	Untreated	Treated		Untreated	Treated
Variance	0.0067	0.0024	Variance	0.0019	0.0013
Observations	4		Observations	4	
T-Stat	0.967		T-Stat	0.810	
T-Critical (2-tail)	2.45		T-Critical (2-tail)	2.45	
P-value (2-tailed)	0.3711		P-value (2-tailed)	0.449	

Table 5.16. Total averages of treated and untreated LCC results for R1/R2, R3 and R4.

Total Average LCC from R1/R2, R3 and R4			
	Experimental Run		
	R1/R2	R3	R4
Treated teams (1&4)	0.044	0.10725	0.056
Untreated teams (2&3)	0.041	0.06975	0.0275

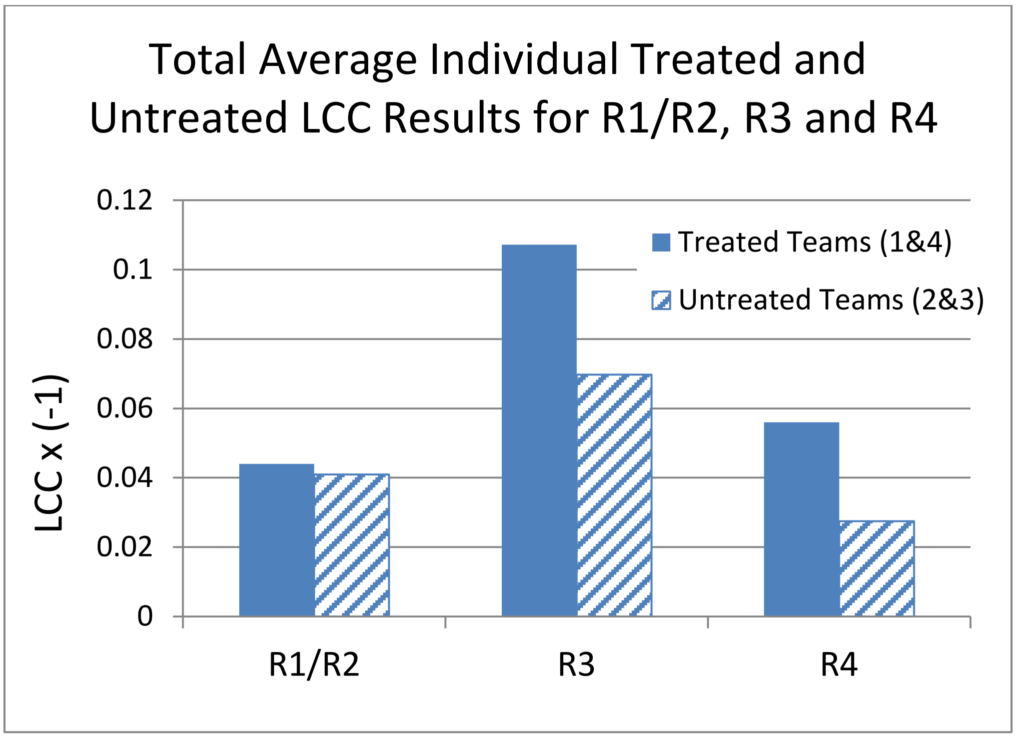

Figure 5.15. Total average individual LCC results from R1/R2, R3 and R4.

The total LCC results graphed in Figure 5.15 clearly shows the overall impact of Standard work and systematic problem solving on the learning outcome from the experiments. The results of the two-sided t-test analysis indicate only the R3 results are statistically significant (see Appendices L through O for the results). In particular, the p-values for R3 are 0.042 and 0.040 for Operator A and Station 1 respectively. All other p-values indicate there is no difference in the data due to treatment.

5.4. The Results of Contextual Learning Curve Analysis of R3 and R4

5.4.1. Total Contextual Relationship of Experimental Learning Curve Results

Up to this point the analysis of the experimental results has considered each run in isolation. For example, all the LC results from R1 and R2 were shown individually, without the additional LCs from R3 and R4. Similarly R3and R4 LCs were also presented separately. A consequence of this was that each individual LCC result was considered an isolated result. In this section, the LCs from all 4 runs will be considered as part of a continuum. In other words, the individual CT data used to construct each LC will be combined to create a relatively complete LC covering all 512 cycles each operator performed at each Station. Within that context, new best-fit lines result in different power equations and therefore different LCCs. The current sub-section contains the contextual LCC results which are followed by the statistical analysis of the LCC results in sub-section 5.4.4. Finally, the comparative analysis of the results will be presented in sub-section 5.4.5. Appendix P contains the complete sets of visual contextual learning curves and the two-sided t-test results of the resultant LCC data obtained from the graphs.

5.4.2. Combined Contextual Learning Curve Results

Figures 5.16 and 5.17 are examples of a visual illustration of the contextual relationships between each experimental run. There are three major components of each graph of this type. The first component consists of the learning curves, obtained directly from the CT data , using the same data as the previous sections. The second component is the best-fit trendlines, and the third is the power equation with the learning coefficient for each trendline. Notice the graph consist of three distinct learning curves. The first curve, from cycle 136-256 is either the R1 or R2 curve, depending on which experimental condition is being evaluated. For example, Figure 5.16 is a graph of the results from team 2 (T2), Station (1), operator B (Operator B). Since operator B only worked in S1 during R2, this data is from R2. If it had been of operator A for S1, it would show R1 data. There is 16 cycle a space between the R1/R2 and R3 learning curve. This is because the first 16 cycles of R3 and R4 were eliminated from the analysis as discussed previously.

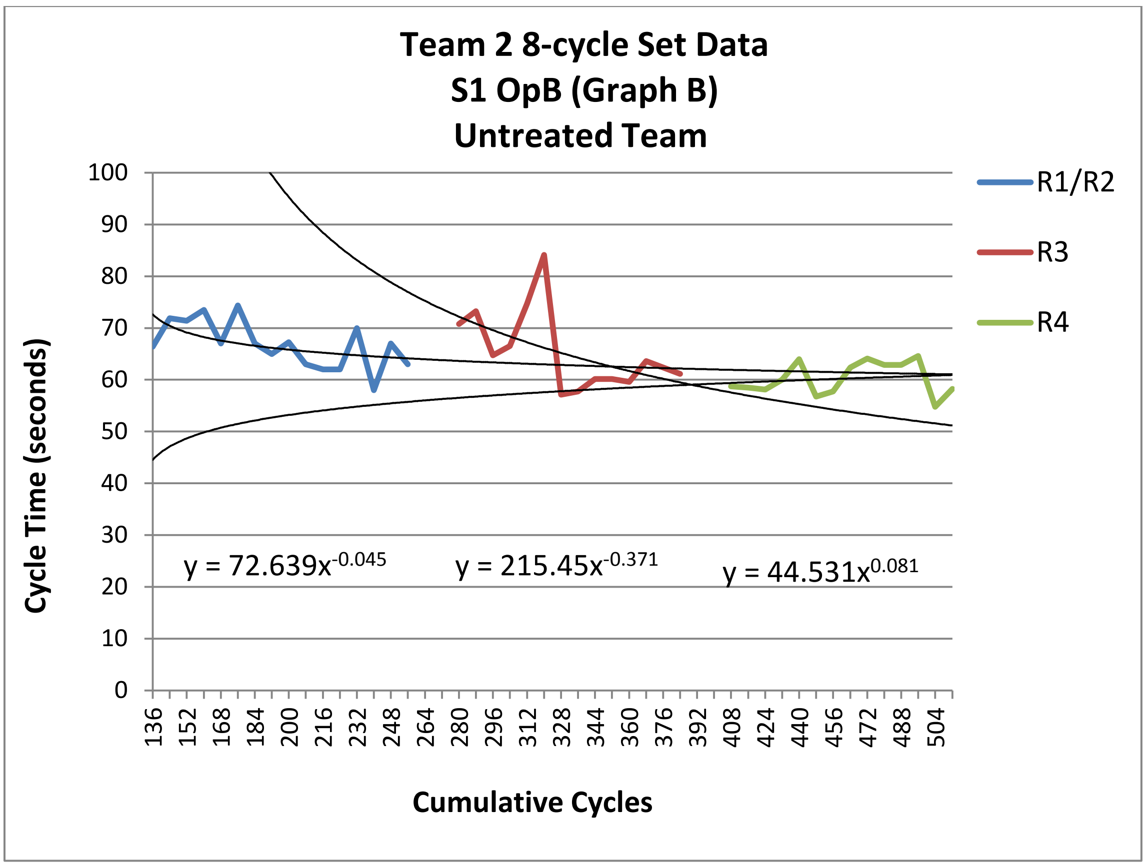

Figure 5.16. Example of a contextual untreated team learning curve set for R1+R2, R3 and R4.

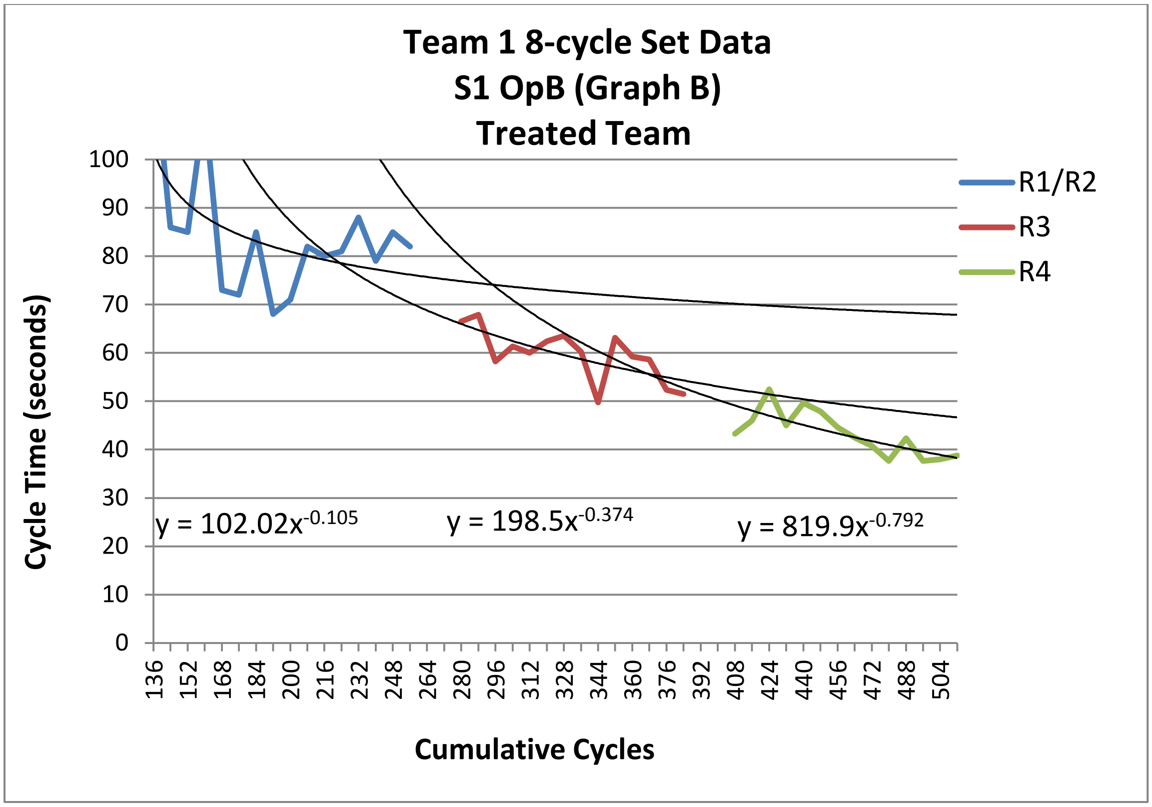

Figure 5.17. Example of a contextual treated team learning curve set for R1+R2, R3 and R4.

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In the continuum of the total learning curve, the R3 data covers cycles 280 to 384. Similarly for the R4 results, there is a 16 cycle gap between the end of the R3 data and the beginning of the R4 data. The R4 data covers cycles 408 to 512. Also as previously discussed, each data point in the learning curves consist of the average an 8-cycle data set. Figures 5.16 and 5.17 provide an illustration of the results from an untreated (Figure 5.16, team 2) and treated (Figure 5.17, team 1) team.

The LCC data obtained from all the contextual learning curves represented by Figures 5.16 and 5.17 are tabulated and presented in Tables 5.17 and 5.18. The R1/R2 results are not included since they have not changed and were previously presented in Tables 5.13 and 5.14. Since 2 dimensions (Operator and Station) of the results are shown in each figure, the tabulated data are segregated to more clearly see the individual learning at each Station and for each operator. The results of operator- specific learning curve analysis from R3 and R4 CT data are presented in Table 5.17. The results are grouped according to group treatment conditions. The LCC data is referred to as "Stable" as a reminder that the LCs were constructed using CT data from the last 112 cycles of each operators 128-cycle run at each Station as mentioned in the previous section (see Experimental Design in Table 3.2).

Table 5.17. Contextual Operator-specific LCC results from R3 and R4.

		R3		R4	
		Stable LC		Stable LC	
		Operator A	Operator B	Operator A	Operator B
team 1	Station 1	-0.605	-0.374	-0.2	-0.792
	Station 2	-0.354	-0.831	-1.017	-0.121
	Avg	-0.4795	-0.603	-0.609	-0.457
team 4	Station 1	-0.689	-0.337	-0.209	-0.35
	Station 2	-0.481	-0.367	-0.57	-0.386
	Avg	-0.585	-0.352	-0.390	-0.368
Total Average		**-0.532**	**-0.477**	**-0.499**	**-0.413**
team 2	Station 1	-0.137	-0.371	-0.266	-0.081
	Station 2	-0.4	-0.616	0.972	-0.371
	Avg	-0.269	-0.494	0.353	-0.226
team 3	Station 1	-0.153	-0.405	-0.746	-0.154
	Station 2	-0.4	-0.337	-0.208	-0.674
	Avg	-0.277	-0.371	-0.477	-0.414
Total Average		**-0.273**	**-0.433**	**-0.062**	**-0.320**

The Station specific data is presented in Table 5.18. Both tables are organized to easily see the average LCC results from both the treated (teams 1 & 4) and untreated teams (teams 2 & 3). The results presented in Tables 5.17 and 5.18 are illustrated graphically in Figures 5.18 and 5.19.

Table 5.18. Contextual Station-specific LCC results from R3 and R4.

		R3		R4	
		Stable LC		Stable LC	
		Station 1	Station 2	Station 1	Station 2
team 1	Operator A	-0.605	-0.354	-0.2	-1.017
	Operator B	-0.374	-0.831	-0.792	-0.121
	Avg	-0.490	-0.593	-0.496	-0.569
team 4	Operator A	-0.689	-0.481	-0.209	-0.57
	Operator B	-0.337	-0.367	-0.35	-0.386
	Avg	-0.513	-0.424	-0.265	-0.478
Total Average		**-0.502**	**-0.509**	**-0.381**	**-0.524**
team 2	Operator A	-0.137	-0.4	-0.266	0.972
	Operator B	-0.371	-0.616	-0.081	-0.371
	Avg	-0.254	-0.508	-0.174	0.301
team 3	Operator A	-0.153	-0.4	-0.746	-0.208
	Operator B	-0.405	-0.337	-0.154	-0.674
	Avg	-0.279	-0.369	-0.450	-0.441
Total Average		**-0.267**	**-0.439**	**-0.312**	**-0.070**

Table 5.19 contains the average LCC results from operator and Station specific conditions respectively based on LCC data presented in Tables 5.13 and 5.14 for individual average LCC results and Tables 5.17 and 5.18 for R3 and R4 average

contextual results respectively. The results are shown graphically in Figures 5.18 and 5.19.

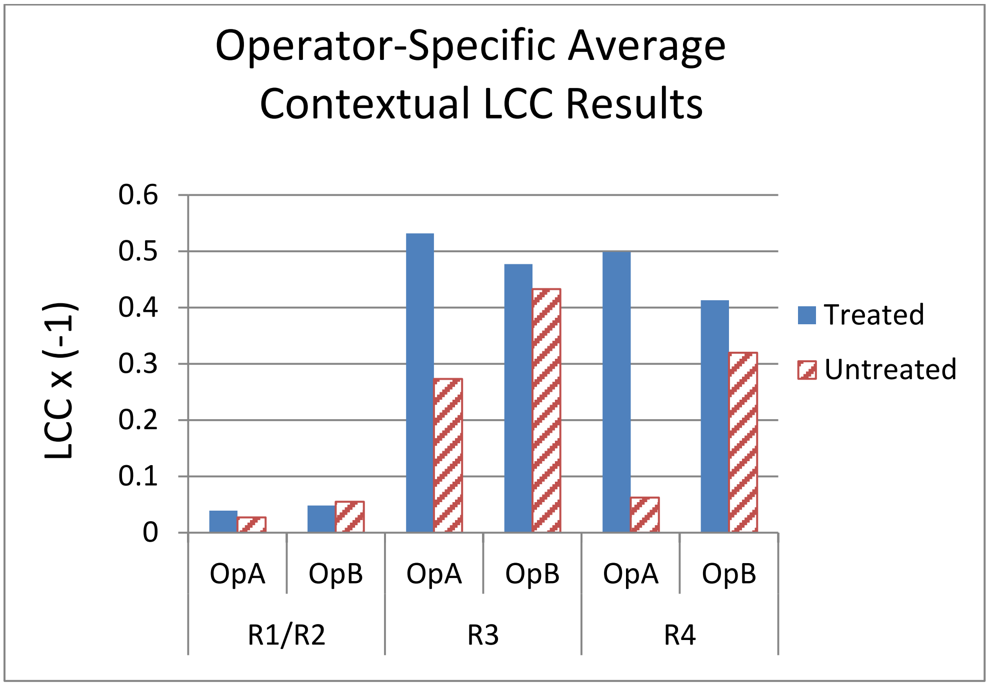

Figure 5.18. Average Operator-specific contextual LCC results for R1/R2, R3 and R4.

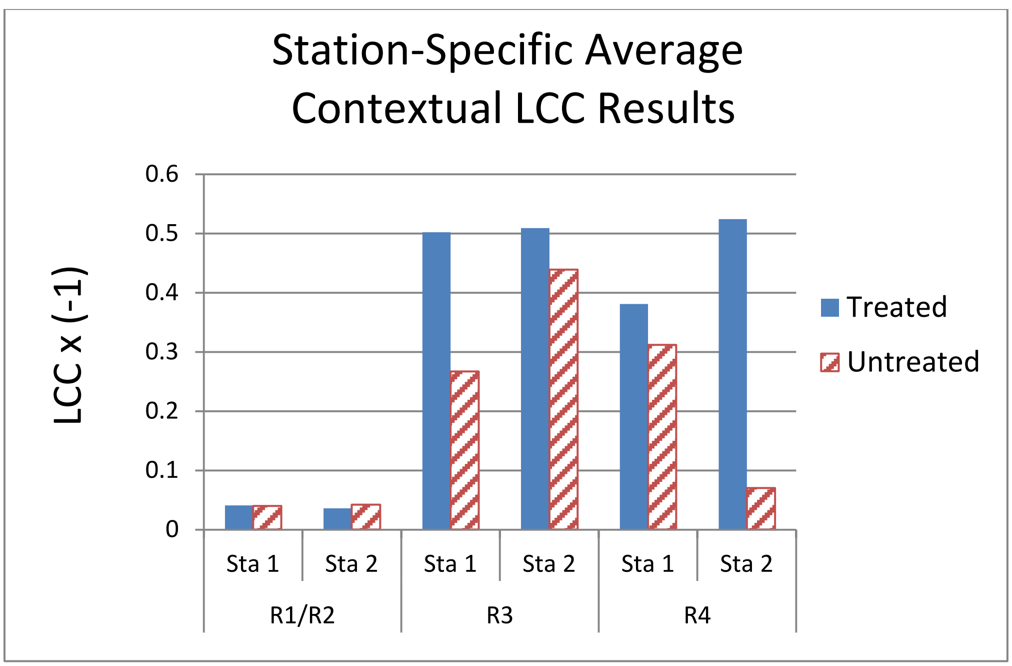

Figure 5.19. Average Station-specific contextual LCC results for R1/R2. R3 and R4.

The total average contextual LCC results were obtained from Tables 5.17 and 5.18 as well as the R1/R2 results from Tables 5.13 and 5.14. The results are presented in Table 5.19 and graphically illustrated in Figure 5.20. The table contains the total average contextual LCC results for the treated and untreated teams. Since the operator-specific results contain both Stations 1 and 2 data, and the Station-specific results contain operator A and operator B data, their totals are equal, as seen in the table. This data provides the basis for the calculated learning ratios (LRs) which will be presented in the next sub-section.

Table 5.19. The combined average operator and Station LCC results from Tables 5.13 and 5.14.

	Operator A + B		Station 1 + 2	
	Average Untreated teams (LCC)	Average Treated team (LCC)	Average Untreated teams (LCC)	Average Treated team (LCC)
R1/R2	-0.042	-0.044	-0.042	-0.044
R3	-0.353	-0.505	-0.353	-0.506
R4	-0.191	-0.456	-0.191	-0.453
Avg R3/R4	-0.272	-0.481	-0.272	-0.480

The results in Table 5.19 are presented graphically in Figure 5.20 to more clearly illustrate the differences in learning rates occurring under each condition. The graph shows the paired LCC results for all four runs and the average for R3+R4 combined. The figure shows how both the treated and untreated groups started at nearly equivalent learning conditions then increased dramatically for both groups in R3 and R4. This is not surprising and there are a couple of possible contributing factors to account for this. The first is the nature of the data sets themselves. Only the last 128 cycles of R1 and R2 were used to construct the LCs and obtain the LCCs. Because R3 and R4 had a job rotation at cycle 129 there was only a total of 128 cycles of CT data from each operator at each Station per runs R3 and R4. Even though the first 16 cycles of R3 and R4 were eliminated from analysis, inspection of the learning curves (Appendices F and G) show there are instances where some settling in may still be occurring, contributing to higher LCC values. Another important factor is the motivation of the operators themselves. At the beginning or R3, all teams were instructed (reminded) they are allowed to make changes after the first 16 cycles. While towards the end of their R1 and R2 runs, they appear to have gotten complacent about their work, During R3 and R4, especially R3 they seem to have observed more potential improvement opportunities and took advantage of them. The biggest difference in the treated and untreated teams was in how they were able to address these opportunities. The critical factor for this study is in the difference in learning corresponding to the differences in how the opportunities were addressed. As shown in Figure 5.20, the overall learning rates for the treated teams, i.e.,, those identifying and eliminating problems via Standard work and systematic problem solving (R3) and waste elimination (R4) were greater than for the corresponding untreated teams.

5.4.3. Comparison of Combined Individual and Contextual Learning Curve Results

The combined results from the individual and contextual approaches to the data are presented in Tables 5.20 and 5.21 and are shown graphically in Figures 5.21 and 5.22 for the operator and Station-specific conditions respectively. The figures clearly show

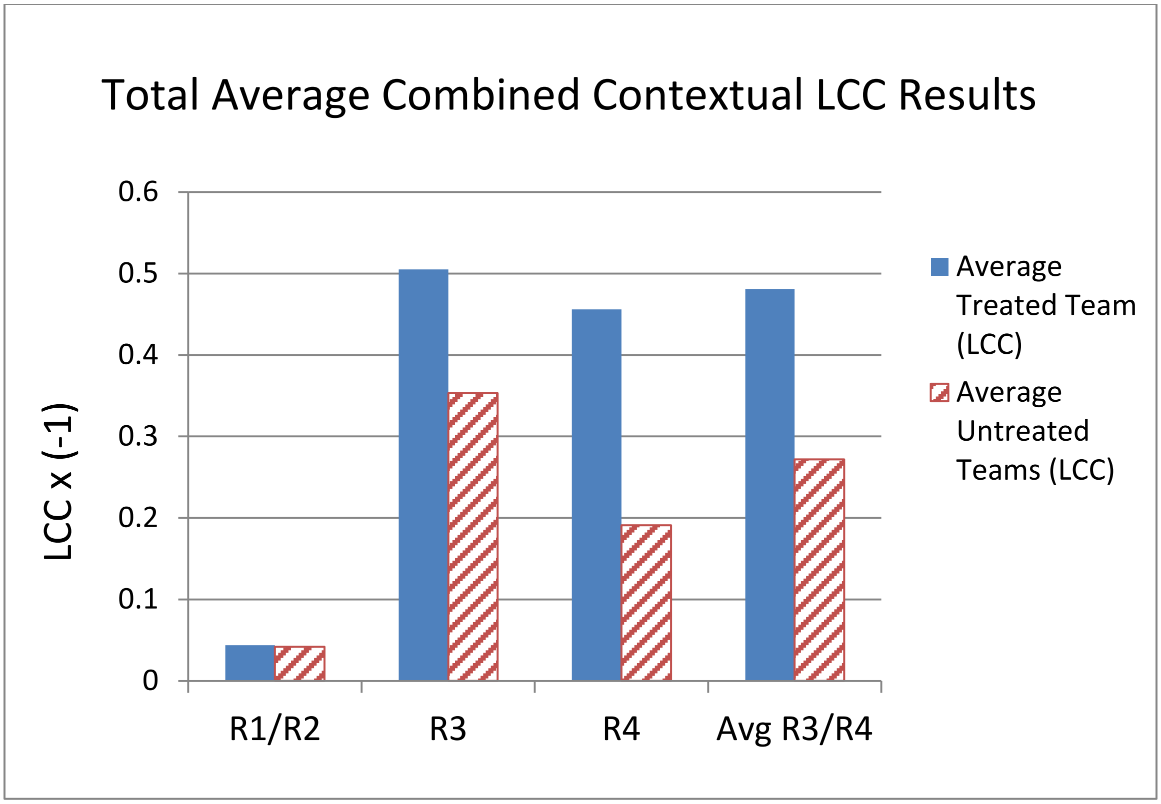

Figure 5.20. The total average combined contextual LCC results for R1/R2, R3 and R4.

the difference between the two approaches for R3 and R4. Although the magnitude of the LCC results differs greatly, the trends in the differences between treated and untreated conditions are similar. In all cases for R3 and R4, the treated teams exhibit greater learning rates than the corresponding untreated teams. The averages of the total combined individual and contextual LCC results are presented in Table 5.22 and shown graphically in Figure 5.23. The next sub-section contains the statistical analysis of the contextual LCC results to determine if they are statistically similar as well.

Table 5.20. The combined Operator-specific average individual and contextual LCC results from R1/R2, R3 and R4.

	R1/R2			
	Individual		Contextual	
	Operator A	Operator B	Operator A	Operator B
Treated	0.039	0.048	0.039	0.048
Untreated	0.027	0.055	0.027	0.055
	R3			
	Individual		Contextual	
	Operator A	Operator B	Operator A	Operator B
Treated	0.114	0.101	0.532	0.477
Untreated	0.057	0.082	0.273	0.433
	R4			
	Individual		Contextual	
	Operator A	Operator B	Operator A	Operator B
Treated	0.054	0.058	0.499	0.413
Untreated	0.02	0.035	0.062	0.32

Table 5.21. The combined Station-specific average individual and contextual LCC results from R1/R2, R3 and R4.

	R1/R2			
	Individual		Contextual	
	Station 1	Station 2	Station 1	Station 2
Treated	0.053	0.036	0.053	0.036
Untreated	0.04	0.042	0.04	0.042
	R3			
	Individual		Contextual	
	Station 1	Station 2	Station 1	Station 2
Treated	0.112	0.104	0.502	0.509
Untreated	0.056	0.084	0.267	0.439
	R4			
	Individual		Contextual	
	Station 1	Station 2	Station 1	Station 2
Treated	0.044	0.068	0.381	0.524
Untreated	0.033	0.022	0.312	0.07

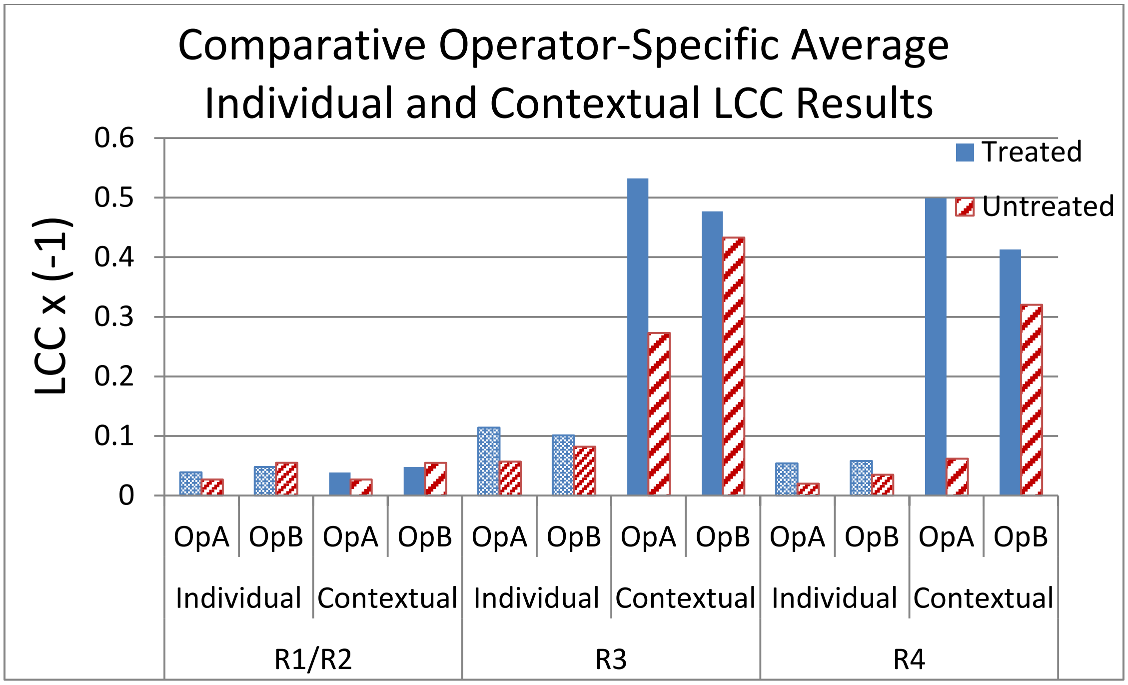

Figure 5.21. Combined average operator-specific individual and contextual LCC results for R1/R2, R3 and R4.

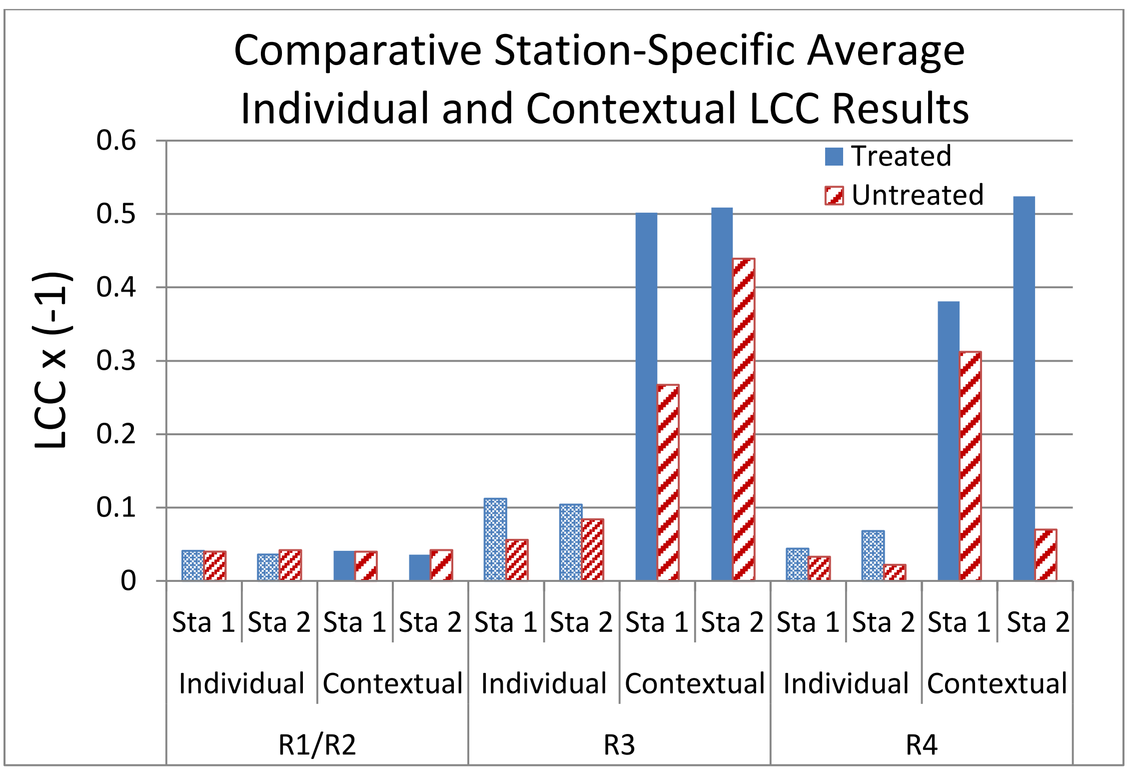

Figure 5.22. Combined average Station-specific individual and contextual LCC results. for R1/R2, R3 and R4.

Table 5.22. The combined total average of the individual and contextual LCC results formR1/R2, R3 and R4.

	Average Total LCC Individual and Contextual Results for R1/R2	
	Individual	Contextual
	Stations 1+2= Operators A+B	Stations 1+2= Operators A+B
Treated	0.044	0.044
Untreated	0.041	0.041
	Average Total Individual and Contextual LCC Results for R3	
	Individual	Contextual
	Stations 1+2= Operators A+B	Stations 1+2= Operators A+B
Treated	0.108	0.505
Untreated	0.070	0.353
	Average Total Individual and Contextual LCC Results for R4	
	Individual	Contextual
	Stations 1+2= Operators A+B	Stations 1+2= Operators A+B
Treated	0.056	0.456
Untreated	0.028	0.191

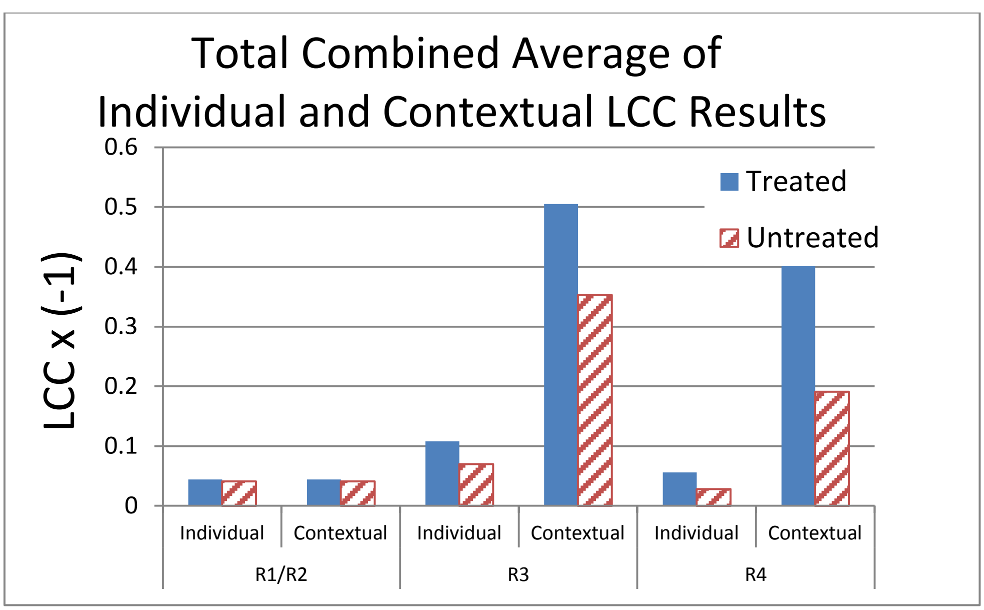

Figure 5.23. Combined average individual and contextual LCC results. for R1/R2, R3 and R4.

5.4.4. Statistical Analysis of Contextual LCC Results

A statistical analysis of the contextual LCC results presented in Tables 5.17 and 5.18 was performed using the Two-Sample t-Test Assuming Equal Variances to determine if the contextual data sets for each condition are significantly different. The complete results are presented for Station and operator-specific conditions in Appendices Q and R respectively, and summarized in Tables 5.23 and 5.24 for Station and operator-specific LCC data respectively.

Table 5.23. Summary of two-sample t-test analysis of contextual Operator-specific LCC data for R3 and R4 treated and untreated teams..

R3 Contextual LCC Data			R4 Contextual LCC Data		
Treated vs Untreated teams			Treated vs Untreated teams		
	Operator A	Operator B		Operator A	Operator B
Observations	4	4		4	4
T-Stat	-2.501	-0.336	T-Stat	-1.058	-0.478
T-Critical (2-tail)	2.45	2.45	T-Critical (2-tail)	2.45	2.45
P-value (2-tailed)	**0.046**	0.748	P-value (2-tailed)	0.331	0.649

Table 5.24. Summary of two-sample t-test analysis of contextual Station-specific LCC data for R3 and R4 treated and untreated teams.

R3 Contextual LCC Data			R4 Contextual LCC Data		
Treated vs Untreated teams			Treated vs Untreated teams		
	Station 1	Station 2		Station 1	Station 2
Observations	4	4		4	4
T-Stat	-2.107	-0.551	T-Stat	-0.372	-1.114
T-Critical (2-tail)	2.45	2.45	T-Critical (2-tail)	2.45	2.45
P-value (2-tailed)	**0.080**	0.601	P-value (2-tailed)	0.723	0.308

As was done previously with respect to the individual R1/R2 and R3/R4 results, the statistical analysis of the contextual data is first performed from the perspective of independent data sets. Therefore, the initial analysis is a two-sided sided t-test comparing treated and untreated R3 and R4 LCC data sets for the operator-specific and Station-specific conditions respectively. According to the analytical results shown in the tables, the treated versus untreated LCC results are significantly different at 4.6% and 8% levels The null hypothesis of the t-test results presented in Tables 5.23 and 5.24 is that the two data sets tested are different, therefore, the higher the p-value from the tests, the less likely the data sets are different respectively.

According to the results summarized in the tables, only the R3 Operator A and Station 1 are statistically significant from each other. This result is similar to the previous two-sided t-test results from the individual LCC data evaluated in sub-section II-D. For convenience, Table 5.25 contains calculated p-values from the combined two-sided t-test results from Table 5.15 for individual R3 and R4 LCC data and the current contextual data results in Tables 5.23 and 5.24. In all cases the number of data points in each set was the same (n = 4). Statistical significant results are highlighted in bold. Although all the tests were performed using alpha = 0.05, the highlighted results range from 0.02 to 0.042 for the individual data and from 0.046 to 0.080 for contextual data. For both data sets the most statistical ly significant differences occur with the R3 operator A and Station 1 results.

In addition to determining the statistical differences between the independent treated and untreated data sets, it is of interest to evaluate the statistical significance of the treatment conditions between the experimental Stages. In particular, the statistical differences for three different cases based on the result of treatments between; A) R1/R2 to R3, B) R3 to R4 and C) R1/R2 to R4 are presented below.

Table 5.25. Cumulative two-sample t-test p-value results for individual and contextual LCC data.

	Cumulative p-Values from Individual and Contextual Two-Sided t-Test Analysis of R3 and R4 LCC Data			
	R3			
	Station 1	Station 2	Operator A	Operator B
Individual	**0.042**	0.467	**0.040**	0.483
Contextual	**0.080**	0.601	**0.046**	0.748
	R4			
Individual	0.704	0.371	0.505	0.449
Contextual	0.723	0.308	0.331	0.649

The following three sub-sections contain the results of paired t-test analysis for each case. In each case, the analysis compares the effects of treatment on paired data, matching specific team, Station and operator LCC results as they progress though the all four runs.

5.4.4.1. Case 1: R1/R2 to R3

The paired t-test results from contextual LCC R1/R2 to R3 are presented in Appendices S and T for Station-specific and operator-specific data respectively. The results show the likelihood of there being a difference in the experimental LCC data obtained in runs 1 and 2 (R1/R2) and R3. The paired p-values are presented along with the average contextual LCC results for R1/R2 and R3 in Table 5.26 and shown graphically in Figure 5.24. Again p-values indicating a statistical ly significant result are highlighted with bold print. The results indicate all the learning curve coefficients (LCCs) obtained from learning curve results of both treated and untreated teams in R1/R2 and R3 are significantly different from their baseline (R1/R2) results at the 95% confidence level.

Table 5.26. Average contextual LCC results and paired t-test p-values from R1/R2 to R3 experimental runs.

	R1/R2		R3		R1/R2 to R3	
	Avg LCC		Avg LCC		p-Value	
	Treated	Untreated	Treated	Untreated	Treated	Untreated
Operator A	0.039	0.027	0.532	0.273	**0.01**	**0.004**
Operator B	0.048	0.055	0.477	0.433	**0.051**	**0.019**
Station 1	0.053	0.04	0.502	0.267	**0.019**	**0.053**
Station 2	0.036	0.042	0.509	0.439	**0.032**	**0.015**

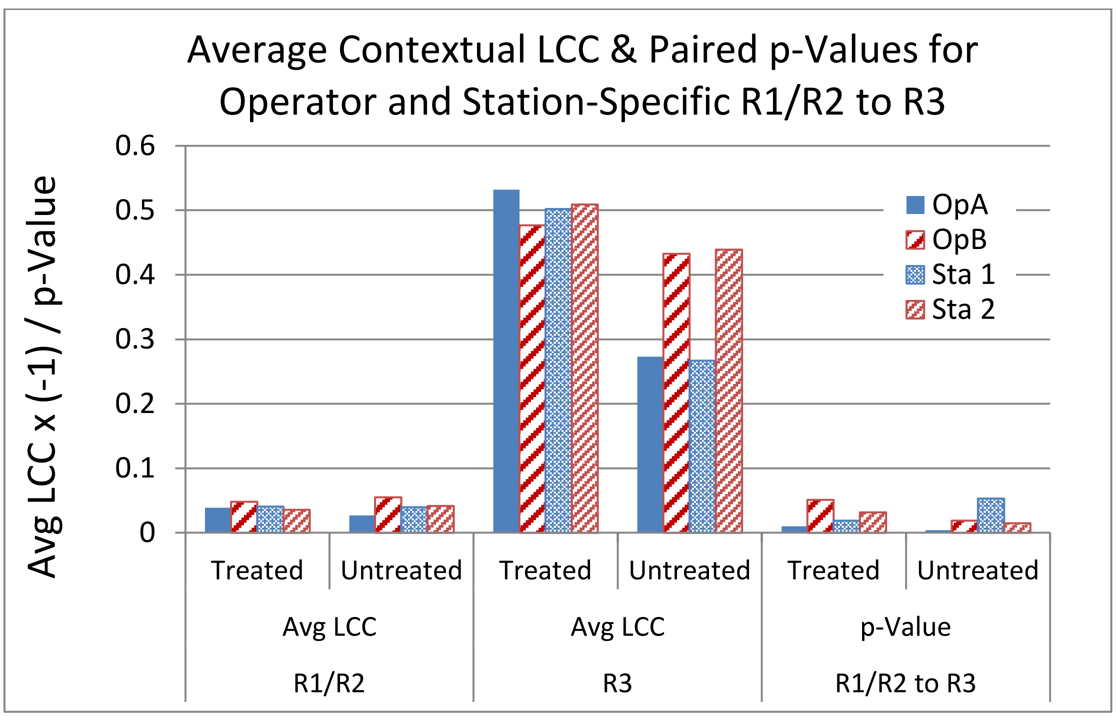

Figure 5.24. Graphical representation of average contextual LCC results and p-value results for R1/R2 and R3 presented in Table 5.25.

From Figure 5.24 it is clear there is a significant difference in the average LCC results for R3 compared to R1/R2 and that according to the p-values, all the teams produced statistical ly different results in R3 compared to R1/R2. As seen previously in Figures 5.16 and 5.17 (pgs 86, 87) in III-A1, both groups exhibited changes in their R3 LCCs compared to their R1/R2 baselines, indicating that regardless of method used, after each team member became an “experienced operator”, they were able to make significant improvements during R3.

5.4.4.2 Case 2: R3 to R4

The paired t-test result from contextual LCC R3 to R4 is presented in Appendices U and V for Station-specific and operator-specific data respectively. The analysis is intended to show the likelihood of there being a difference in the experimental LCC data obtained in R3 and R4. The paired p-values are presented in Table 5.27 and shown graphically in Figure 5.25. The results indicate the learning curve coefficients (LCCs) obtained from learning curve results in R3 and R4 are not significantly different at the 95% confidence level. However, the data indicates there is an apparent difference between both the magnitude of learning and in the consistency of it.

Table 5.27. Average contextual LCC results and Paired t-test p-values from R3 to R4 experimental runs.

	R3		R4		R3 to R4	
	Avg LCC		Avg LCC		p-Value	
	Treated	Untreated	Treated	Untreated	Treated	Untreated
Operator A	0.532	0.273	0.499	0.062	0.908	0.213
Operator B	0.477	0.433	0.413	0.320	0.80	0.509
Station 1	0.502	0.267	0.381	0.312	0.623	0.84
Station 2	0.509	0.439	0.524	0.070	0.96	0.381

The treated teams appear to experience higher learning rates which are also more evenly distributed than for their untreated counterparts. The p-values comparing the difference in the R3 to R4 LCC results also indicate there is a higher degree of similarity between the treated team results compared to the untreated teams. This indicates that while there is more learning occurring in the treated group, it is also more evenly distributed between R3 and R4.

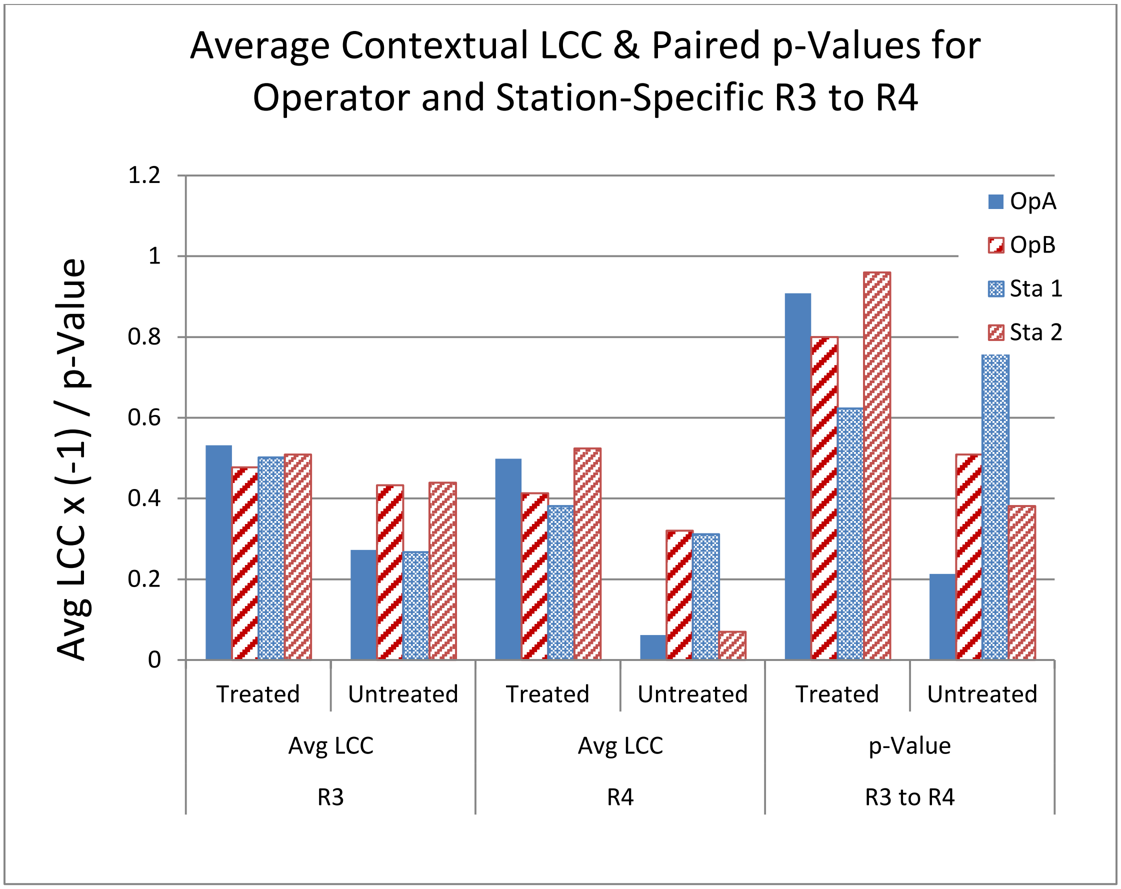

Figure 5.25. Graphical representation of average contextual LCC results and p-value results for R3 and R4 presented in Table 5.26.

5.4.4.3. Case 3: R1/R2 to R4

The complete paired t-test results from contextual LCC R1/R2 to R4 are presented in Appendices W and X for Station-specific and operator-specific data respectively. The paired p-values are presented in Table 5.28 and are shown graphically in Figure 5.26. The results indicate the learning curve coefficients (LCCs) obtained from learning curve results in R1/R2 and R4 are significantly different at a less than 90% confidence level for all conditions evaluated in t the treated samples and for Operator B and Station 1 for the untreated teams. The figure also shows the magnitude of the LCC data for the treated teams are generally larger than the corresponding untreated team results in R4. In addition, while all four treated conditions (operators and stations) exhibited relatively higher LCCs than their untreated counterparts, they are once again more consistent that the corresponding untreated R4 LCC results.

Table 5.28. Paired t-test p-values from contextual LCC data obtained from R1/R2 to R4 experimental runs.

	R1/R2		R4		R1/R2 to R4	
	Avg LCC		Avg LCC		p-Value	
	Treated	Untreated	Treated	Untreated	Treated	Untreated
Operator A	0.039	0.027	0.499	0.062	**0.084**	0.928
Operator B	0.048	0.055	0.413	0.320	**0.054**	0.106
Station 1	0.041	0.04	0.381	0.312	**0.06**	**0.074**
Station 2	0.036	0.042	0.524	0.070	0.96	0.939

In summary, based on the results of the three cases presented, in Case 1 (Figure 5.24), there is no apparent difference between the treated and untreated results in R1/R2.

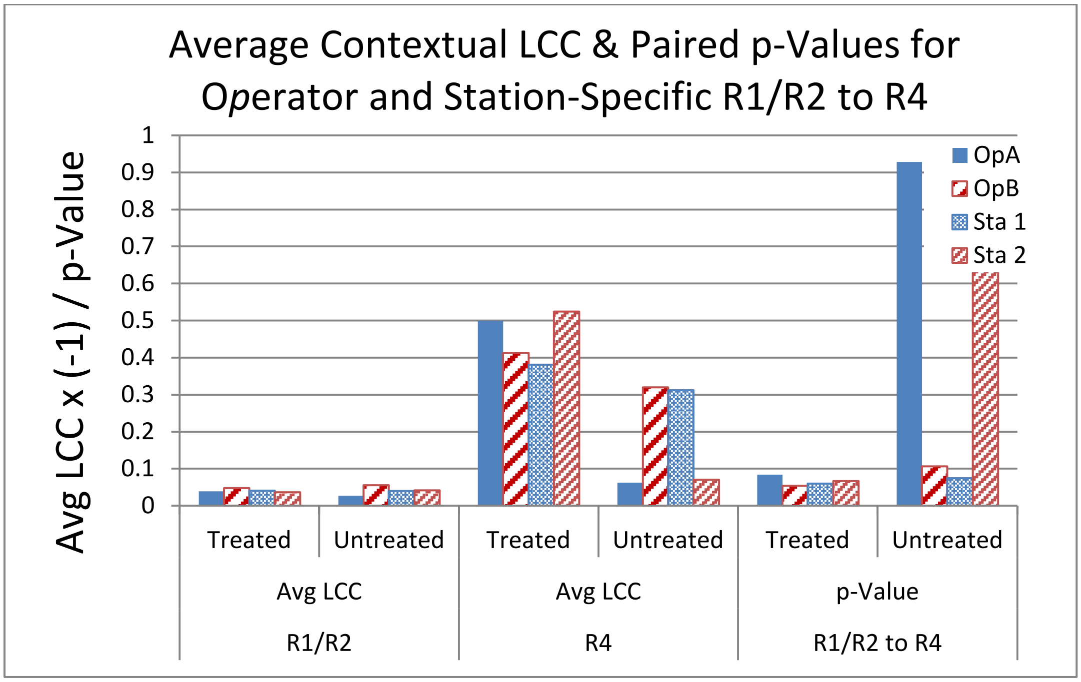

Figure 5.26. Graphical representation of average contextual LCC results and p-value results for R3 and R4 presented in Table 5.28.

This is as expected since only the last 128 cycles of R1 and R2 were used in the analysis and no treatments were given during those runs. R3 was performed about a week after the completion of R2 and it seems even though the first 16 cycles were eliminated from the analysis, all the operators were motivated to make changes to their work if they perceived any problems. Additionally, both groups were instructed to make “improvements” they saw were needed to reduce their individual cycle times. During R3 the difference between the treated and untreated teams was in the way their opportunities for improvement or problems were identified and addressed. For the untreated teams, problem identification was not formalized or systematic and therefore it was left up to the individual operators to identify and develop work- arounds. For the treated teams, their work was defined by Standard work before R3 began, (i.e.,, the operators on these teams identified their normal work), and during the course of R3 they addressed abnormal occurrences or things which prevented them from performing their Standard work. It appears likely that because of potential “low hanging fruit” occurring in the working conditions of both treated and untreated teams after completion of R1 and R2 both groups made significant changes and experienced considerable learning relative to the baseline runs.

For Case 2 (Figure 5.25), the statistical results indicate there is no significant difference between the results of either group. However, there does appear to be a relatively consistent trend indicating a greater difference between the treated versus the untreated team results. Of the four conditions examined in Case 2, the LCC data for treated teams from R3 and R4 exhibit greater similarities to each other than do their untreated counterparts. The similarity is an indication there were similar degrees of learning occurring during both runs. In the next section these similarities will be correlated with the LCC results to get a clearer picture of the effect.

Finally in Case 3 (Figure 5.26) the range of p-values indicates there is a significant difference between the results from Station 2 and Operator A of the untreated groups compared to their treated counterparts. In particular, the high p-values give a strong indication there is no difference in the learning occurring in R1/R2 and R4 for untreated Operator A at Station 2. Conversely, the low p-values for the remaining conditions indicate there is significant difference in the learning outcomes of both treated operators and Stations and most likely one untreated operator and Station based on the current number of samples.

5.4.5. Comparative Analysis of Contextual LCC Results

The contextual operator and Station-specific LCC results for R1, R2 R3 and R4 are presented in Table 5.29. The data presented in Table 5.29 is graphed in Figures 5.27 and 5.28 for operator and Station-specific results respectively. As previously mentioned, operator and Station-specific results from R3 and R4 include data obtained while the operator worked at both Station 1 and 2. The operator-specific results show a clear trend in increased average LCC values for treated versus untreated operators R3 and R4. The results indicate that the rate of learning is greater for operators in the treated condition than in untreated one. The Station-specific results can be seen in Figure 5.28. Not surprisingly, the results are similar to those from the operator-specific results.

Table 5.29. Combined average contextual operator-specific and Station-specific LCC results from R1/R2, R3 and R4.

	Operator A		Operator B	
	Average Untreated teams (LCC)	Average Treated team (LCC)	Average Untreated teams (LCC)	Average Treated team (LCC)
R1/R2	-0.027	-0.039	-0.055	-0.048
R3	-0.273	-0.532	-0.433	-0.477
R4	-0.062	-0.499	-0.320	-0.413
Avg R3/R4	-0.168	-0.516	-0.377	-0.445
	Station 1		Station 2	
	Average Untreated teams (LCC)	Average Treated team (LCC)	Average Untreated teams (LCC)	Average Treated team (LCC)
R1/R2	-0.040	-0.053	-0.042	-0.036
R3	-0.267	-0.502	-0.439	-0.509
R4	-0.312	-0.381	-0.070	-0.524
Avg R3/R4	-0.290	-0.442	-0.255	-0.517

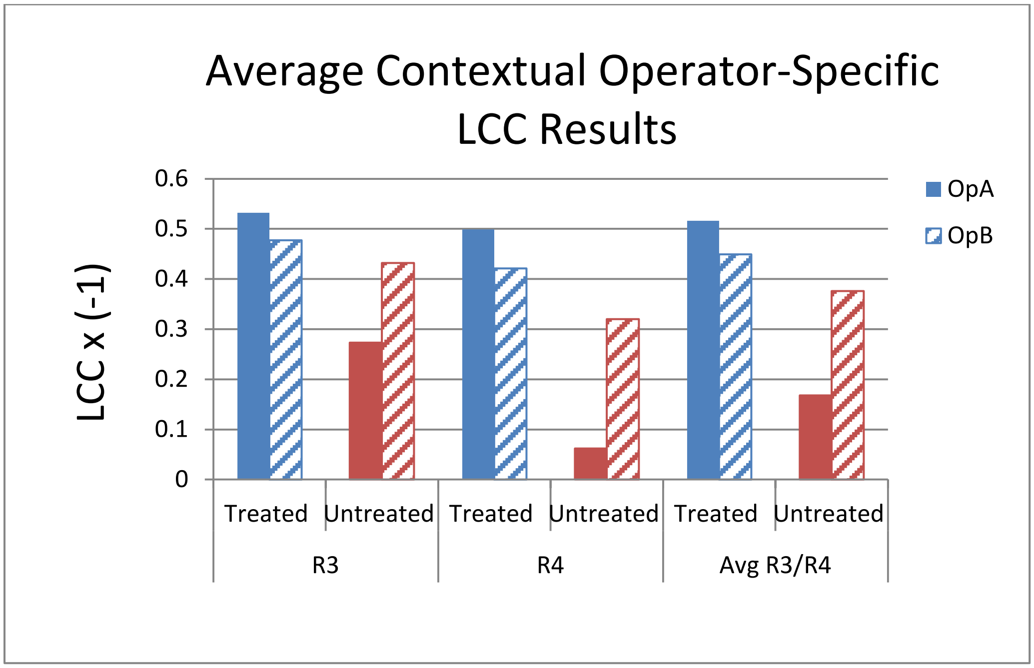

Figure 5.27. Average Operator to Operator Learning Curve Constant (LCC) results taken from individual operators A and B for treated and untreated teams.

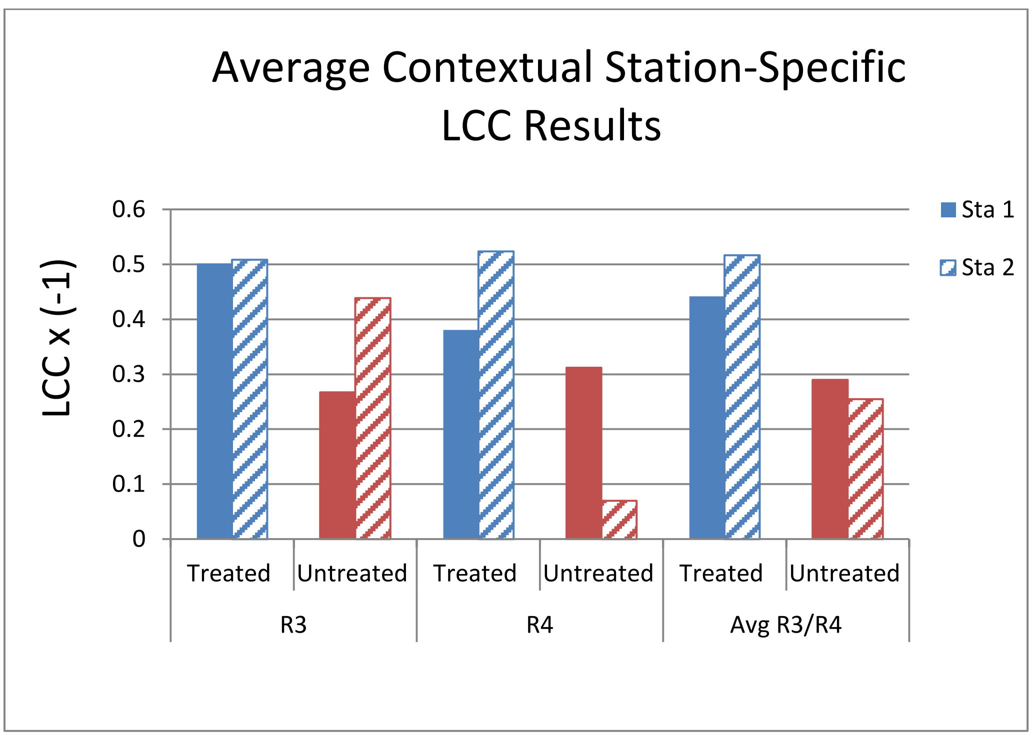

Figure 5.28. Average Station to Station Learning Curve Constant (LCC) results from treated and untreated teams.

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The operator and Station-specific results also indicate the amount of variation in learning rates between the treated and untreated groups are also different. The contextual operator and Station-specific differences based on treatment observed in Figures 5.27 and 5.28 are more clearly illustrated in terms of percentage in Figures 5.29 and 5.30. These figures show the percent difference between the treated and untreated results in R3, R4, and their average (R3/R4), for operator and Stations-specific LCC results respectively. The uneven distribution of learning between operators in the untreated teams can be clearly seen. Learning rates (LCCs) differences between untreated operators A and B range up to 4 times the differences seen between the operators in the treated teams. It is possible, given the small sample size, that the actual differences are not as large as that

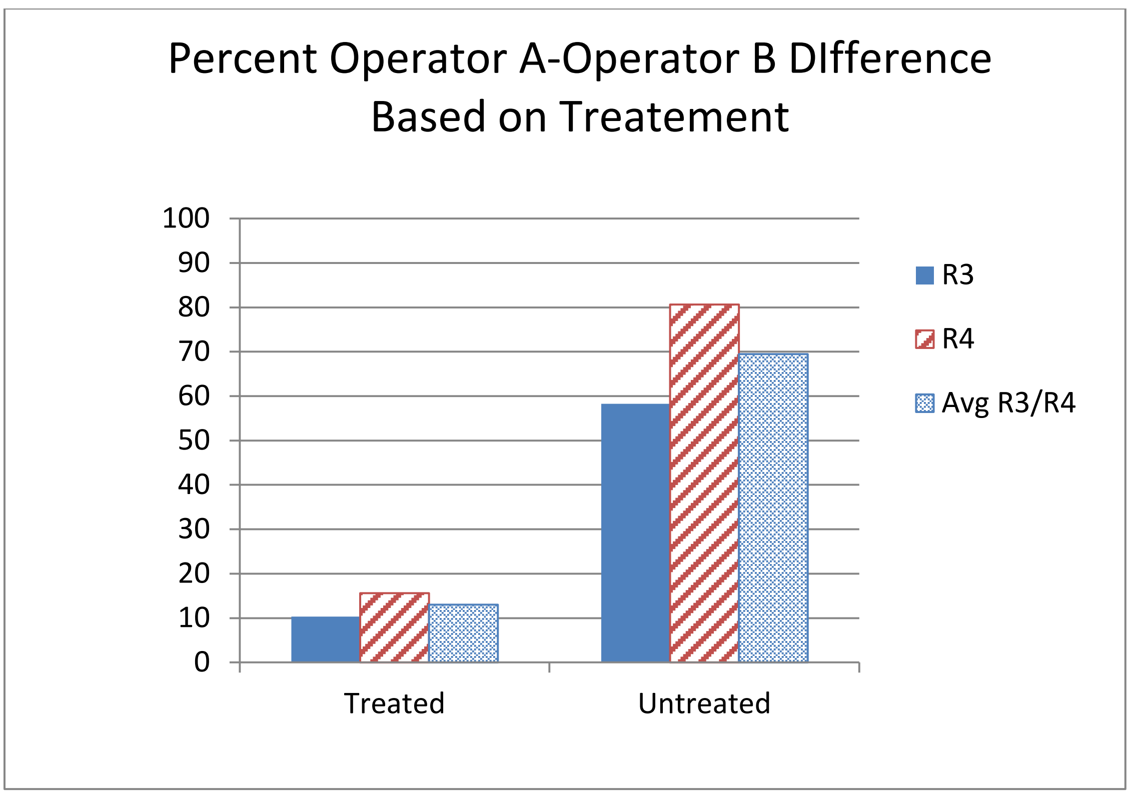


Figure 5.29. Operator to operator percentage differences for R3, R4 and average R3 and R4 combined results.

seen in R4, however, the data does support a conclusion there is greater learning rate variation between operators in the untreated condition than with the treated one. This conclusion is further supported by the Station-specific results presented in Figure 5.30.The average percent difference between the LCCs from Station 1 and Station 2 for the treated and untreated teams varies from 20% to &0% for the treated and untreated teams respectively.   The represents a 3.5-fold difference based on treatment condition. The differences in learning seen in the results presented here support earlier findings by other researchers that learning is not evenly distributed across organizations, even when they are doing the same work (Argote, 1999).

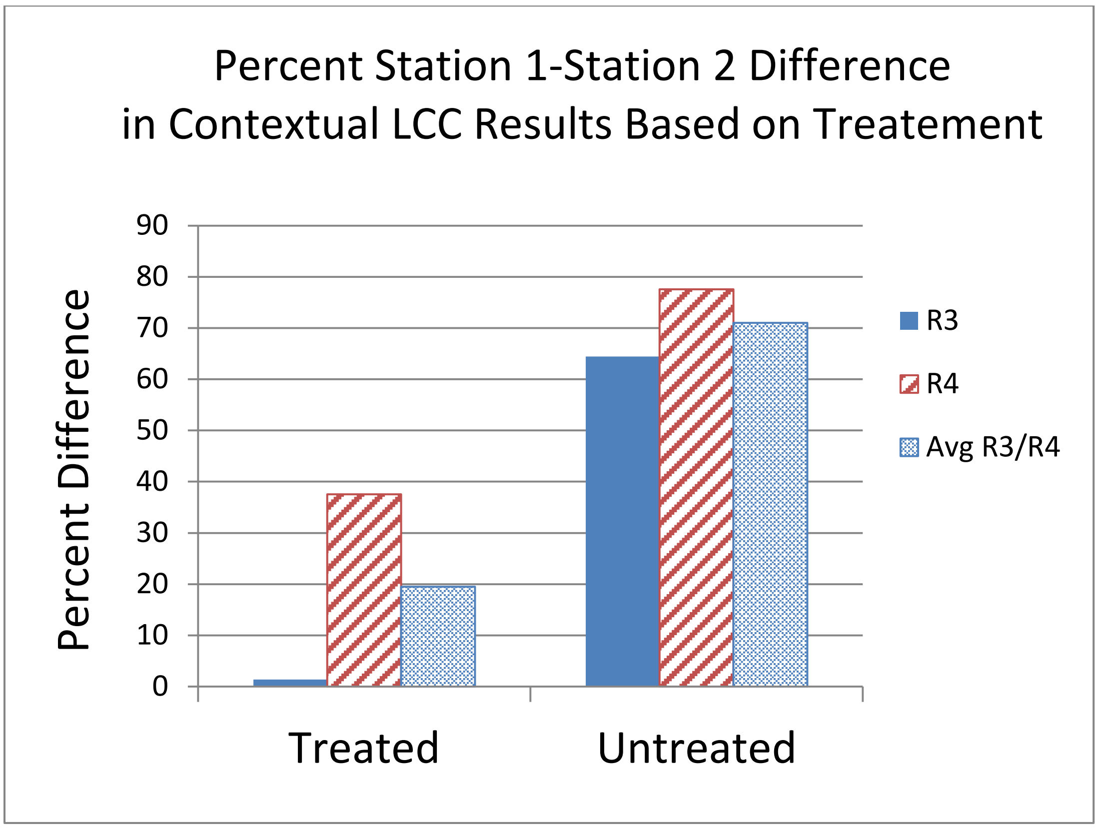


Figure 5.30. Station to station percentage differences for R3, R4 and average R3 and R4 combined results.

5.4.6. Learning Ratios Obtained from Total Average Contextual LCC Results

One method which can be used to describe the differences in learning rates observed between the treated and untreated teams is to calculate a learning ratio (LR) based on the LCC results. The total average contextual LCC results listed in Table 5.22 are presented in Table 5.30 and graphically illustrated in Figure 5.31. From the results listed in Table 5.30, the ratios of the R3 or R4 LCC results to the baseline (Avg R1/R2) were calculated and are listed in Table 5.31. As seen in the table, once the LCC ratios have been determined, the ratio of the treated to untreated LCC ratios can be calculated.

Table 5.30. Total average contextual LCC results.

Total Combined Average Contextual LCC Results				
	R1/R2	R3	R4	Avg R3/R4
Treated	0.044	0.505	0.456	0.481
Untreated	0.041	0.353	0.191	0.272
T/UT	1.07	1.43	2.39	1.77

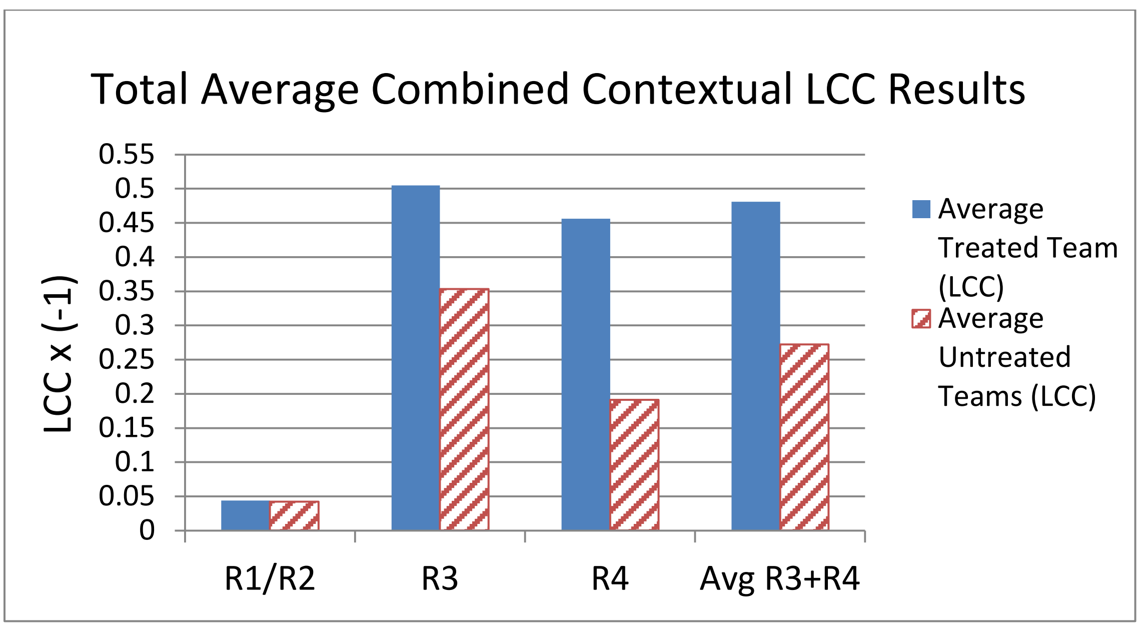


Figure 5.31. The total average combined contextual LCC results for R1/R2, R3 and R4.

Table 5.31 LCC ratios calculated from LCC results presented in Table 5.30.

	R3 / (Avg R1+R2)	R4 / (Avg R1+R2)	R3 / R4	(Avg R3+R4) / (Avg R1+R2)
Treated teams	11.5	10.4	1.1	10.9
Untreated teams	8.6	4.6	1.9	6.6

Table 5.32. Normalized LCC results on a scale of 1 to 10 from Table 5.31.

	R3 / (Avg R1+R2)	R4 / (Avg R1+R2)	R3 / R4	(Avg R3+R4) / (Avg R1+R2)
Treated teams	.825	.738	0.0	.778
Untreated teams	.595	.278	0.06	.437

The LCC ratios introduced in Table 5.31 were normalized and are presented in Table 5.32 and graphically illustrated in Figure 5.32. The graph shows both groups experienced relatively high rates (LCCs) during R3. However, the is an approximate 25% decrease in the learning rates for untreated teams compared to the treated teams during R3. The results indicate that it is more effective to focus activities on removing challenges to Standardization using systematic problem solving than to rely on individual efforts for improvement. In R4 there is an even greater difference. Although the treated teams exhibit a 10% decrease in the LCC ratio from the R3/R1+R2 level, the untreated group experienced more than 30% decrease, resulting in a total difference of 46% in favor of the treated teams. The LCC ratio for R3/R4 in the figure shows about a 2:1 increase in the untreated group over the treated group. This result is a measure of the difference in learning rates measured in R3 and R4 for the two groups.

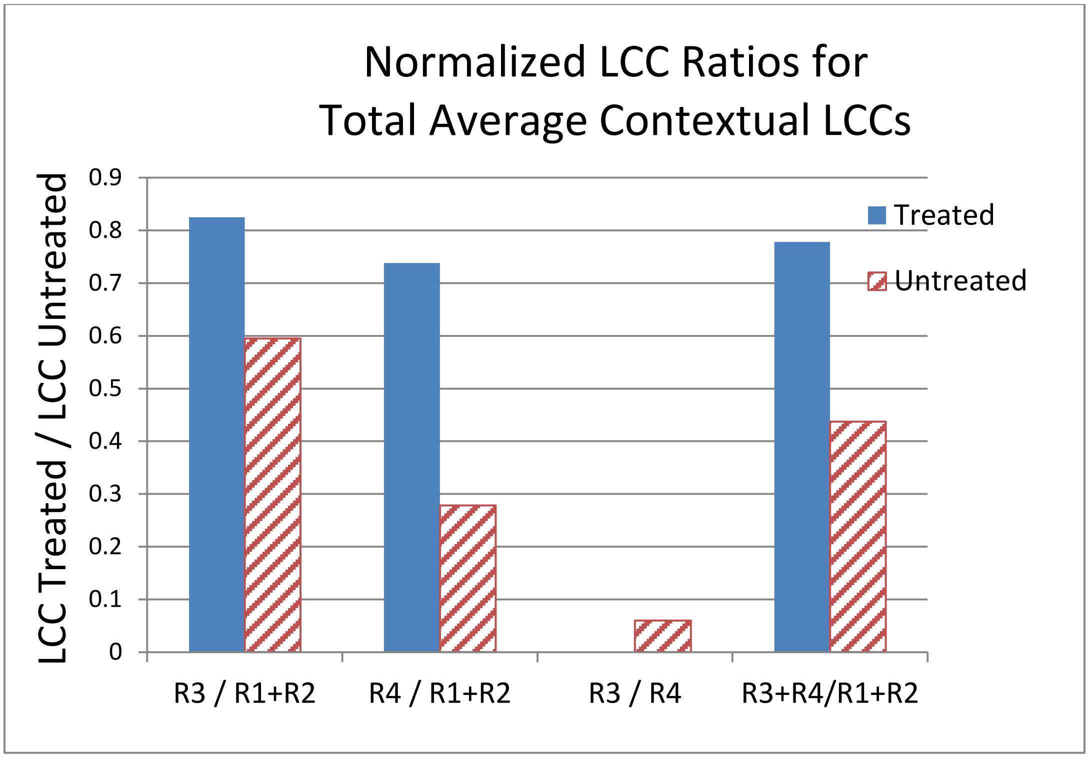


Figure 5.32. Normalized LRs for treated and untreated teams.

As noted above, the untreated LCC ratio decreased from about 0.6 for R3/(avg R1+R2) to 0.28 for R4/(Avg R1+R2) or by about 32%, while the treated group only decreased from 0.83 to 0.74 or by 9% for the same runs. Finally, the LCC ratios based on the average of R3 and R4 shows an approximate 35% overall decrease in the total learning rates for treated teams over untreated teams in general for the treated runs combined.

As previously mentioned, learning ratios (LRs) are determined from the ratio of treated to untreated LCCs for a particular run(s). The learning ratios (LR) from average experimental LCC results are included in Table 5.30 for each condition (R1/R2, R3, R4 and R3/R4). The LRs from Table 5.30 are shown graphically in Figure 5 .33. In this figure, as in the previous Figure 5.32, normalization makes it easy to speak in terms of percentages. The total range of the vertical axis is 100%. Using this interpretation for simplicity, the figure shows an approximate 15% increase in learning rate associated with the treated group for R3 over the untreated group. In other words, focusing on performing normal work and eliminating the abnormal occurrences using collaborative systematic problem solving resulted in a 15% higher rate of learning in R3 than simply making improvements based on individual and independent operator actions using non-systematic problem solving. In R4, the difference nearly quadruples. Treated teams are using collaborative systematic problem solving to eliminate formally recognized wastes (Toyota's 7 wastes and muri (over burden) and mura (fluctuation). In contrast, untreated team members continue working independently on making improvements on problems they identify. However, by the end of R4, each team has built 1024 cylinders, but because there is no formalized mechanism to help guide improvements, by R4 they are simply concentrating on getting the work done.

Finally, touching base with reality in some respects, Figure 5.34 shows the average total changes in cycle time which occurred for the treated and untreated teams. The increased learning rates exhibited in R3 and R4 translate into real performance improvements.

While both groups significantly decreased their cycle times compared to the initial times, the treated group shows an additional 7% improvement in R3, totally in a 25% decrease in individual process cycle time over the average of the first two runs (R1 and R2). As seen in Figure 5.32 the TLR for treated R4 teams was nearly twice the amount seen for untreated teams going from about 13% to 25%.

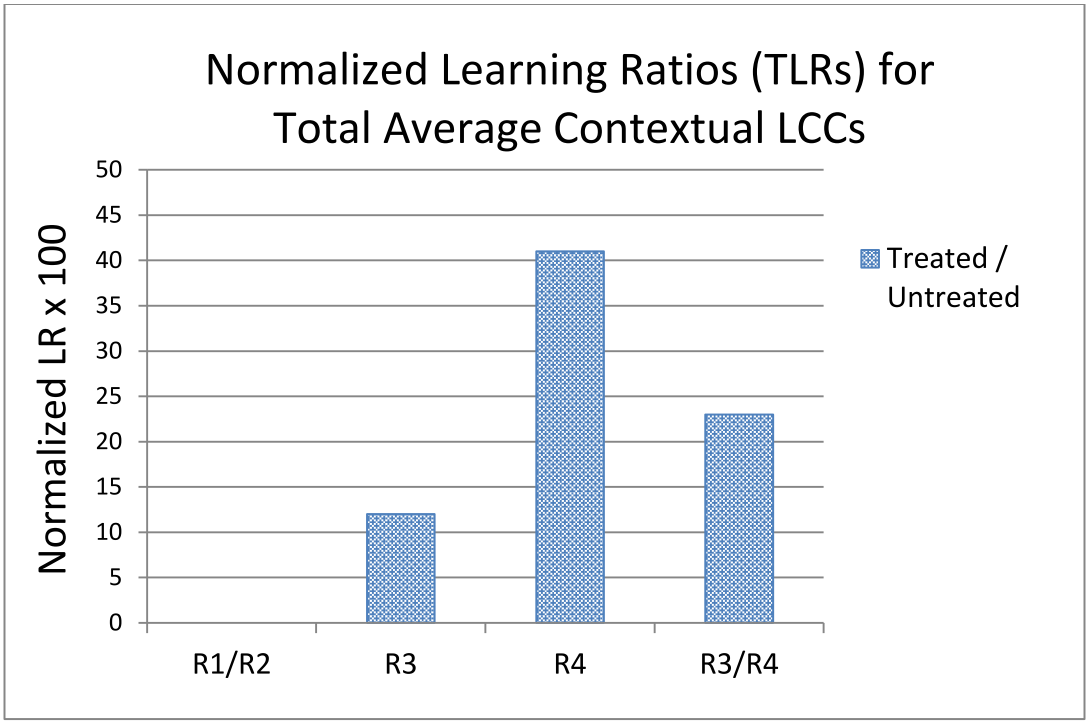


Figure 5.33. The total learning ratios (TLRs) for treated and untreated teams

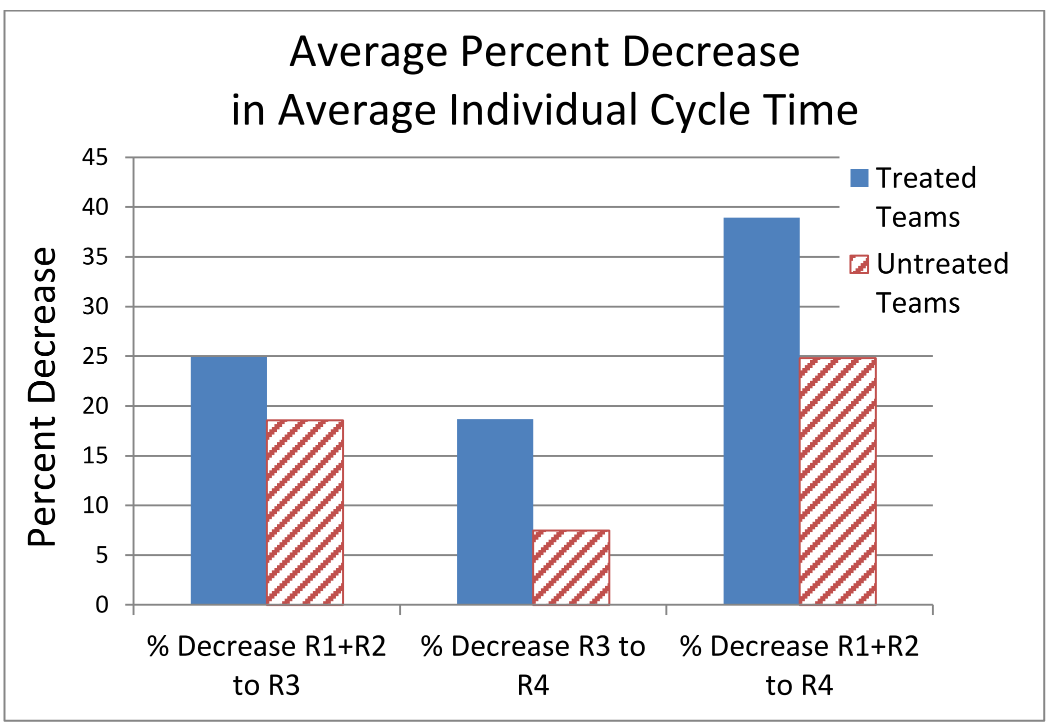


Figure 5.34. Average percent change in cycle time for treated and untreated teams.

The increase in the LR indicates an increased difference in the LCCs for the two groups goi9ng form R3 to R4. Therefore, even though there is an overall decrease in LCC for both groups, the decrease experienced by the untreated group was much greater (about 2 times as seen in Figure 5.33 going from 13% TLR to 25%). According to Figure 5.34, this corresponded to an additional decrease in CT from R3 by about 19% and 7% respectively.

5.5. The Effects of Treatment on Total Cycle Time and Throughput Time

5.5.1. Introduction

In Section 5.4 the total cycle time and total throughput time per cycle (unit produced) will be evaluated. Up to this point the basic unit of analysis has been 8-cycle CT data from individual Stations/operators. No performance data has been analyzed because the basic unit of analysis is a single Station or operator. Both total cycle time (TCT) and total throughput time (TPT) use the combined CT or performance of both Stations in series as the basic unit of analysis. The results of the contextual LCC analysis presented in Section III-A4 show a trend towards increased learning rate consistency between the treated team members compared to the untreated team members. Using the (TCT) and (TPT) results it is possible to see the effect of treatment on the previously observed trends towards increased learning consistency and performance via the impact of systematic problem solving for Standardization and waste elimination on cycle time (CT).

Because each operator works in isolation, especially during R1/R2 and because there is WIP (work in process) between each Station, the fastest operators are able to work ahead of their partners. Over time this creates imbalances, allowing the faster operator to finish first, creating wait time (WT) while the other operator completes his/her work. The experimental design divided each run into 16-cycle segments. One reason for this was to allow slower operators to catch up in order to limit the amount of time they fell behind; otherwise unpredictable amounts of WIP would be required for the experiments instead of the 4 equivalent units of material actually designed in. TCT and TPT data can be used to determine the system performance and correlating it with learning rates for the coupled CT (both Stations in series).

5.5.2. Total Cycle Time (TCT) CT Analysis

Adding the individual 8-cycle CT data from Stations 1 and 2 together gives the total CT (TCT) per 8-cycle unit. Averaging all 32 sets per run gives the TCT for that run or operator order. The results of these calculations, which do not include WT, are presented in Table 5.3. In Table 5.33 the TCT per cycle data is presented in terms of both the OpA+OpB and OpB+OpA conditions which show the difference in results based on the operators positions in the system. For example, OpA+OpB refers to the condition where Operator A performs the work at Station 1 and Operator B is at Station 2 and references to OpB+OpA refers to the opposite condition. The differences between the performances under these two conditions could provide some insight into the effects of treatment on the ability of operators to perform each other's work, which could significantly impact system synchronization in larger production systems. Figure 5.35 shows the average TCT for both operator orders from the treated and untreated teams from Table 5.33for each run taken. As before, R1 and R2 are grouped together because together they represent the baseline condition. Because the results shown are averages, they represent both operator order conditions in all runs. The figure shows how TCT decrease for both groups as they progressively gain experience moving from R1/R2 to R3 then R4.

Table 5.33. Average total cycle time (TCT) per cycle for R1, R2, R3 and R4.

	R1 (sec)	R2 (sec)	Avg R1+R2 (sec)	R3 (sec)	R4 (sec)
T1					
OpA+OpB	122		122	98	89
OpB+OpA		150	150	92	87
T4					
OpA+OpB	148		148	109	90
OpB+OpA		117	117	98	92
Average Treated	**135**	**134**	**135**	**99**	**90**
T2					
OpA+OpB	138		138	116	104
OpB+OpA		125	125	112	105
T3					
OpA+OpB	159		159	133	118
OpB+OpA		178	178	143	132
Average Untreated	**149**	**152**	**151**	**126**	**115**

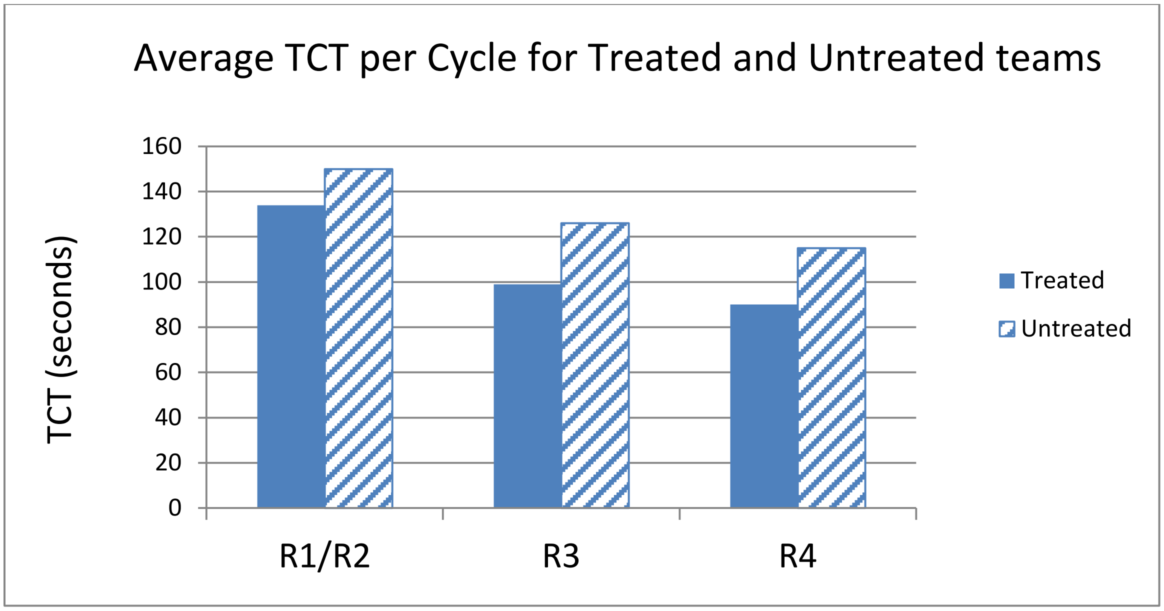


Figure 5.35. The average TCT per cycle based on both operator order conditions for treated versus untreated teams in R1/R2, R3 and R4.

The operator order-specific TCT CT data presented in Table 5.33 was used to calculate the differences between OpA+OpB and OpB+OpATCT CT and tabulated in Table 5.34. Examining the difference between the OpA+OpB and OpB+OpA operator order conditions provides an indication of how uniformly each team member (TM) performs at each Station. The differences in TCT CT data due to operator order are presented in Figure 5.36. From the figure, even though the difference in TCT due to operator position was initially 30 seconds for the treated teams versus only about 15 seconds for the untreated teams. The differences decreased rapidly in R3 and by even more in R4. In R3 both the treated and untreated groups had very similar TCT results which were due to decreases of about 22 seconds for the treated teams and about 10 seconds for the untreated ones. In R4, while the difference in operator TCT of the treated teams continued to decrease, to about 2 seconds, for untreated operators it remained at about the same level or higher, indicating a leveling off of the effects of individually based non-systematic improvement activity.

Table 5.34. The absolute difference in TCT per cycle for OpA+OpB and OpB+OpA.

	The Absolute Difference TCT per Cycle in OpA+OpB and OpB+OpA		
	R1/R2	R3	R4
T1	28	6	2
T4	31	11	2
Avg Treated	**30**	**9**	**2**
T2	13	4	1
T3	19	10	14
Avg Untreated	**16**	**7**	**8**

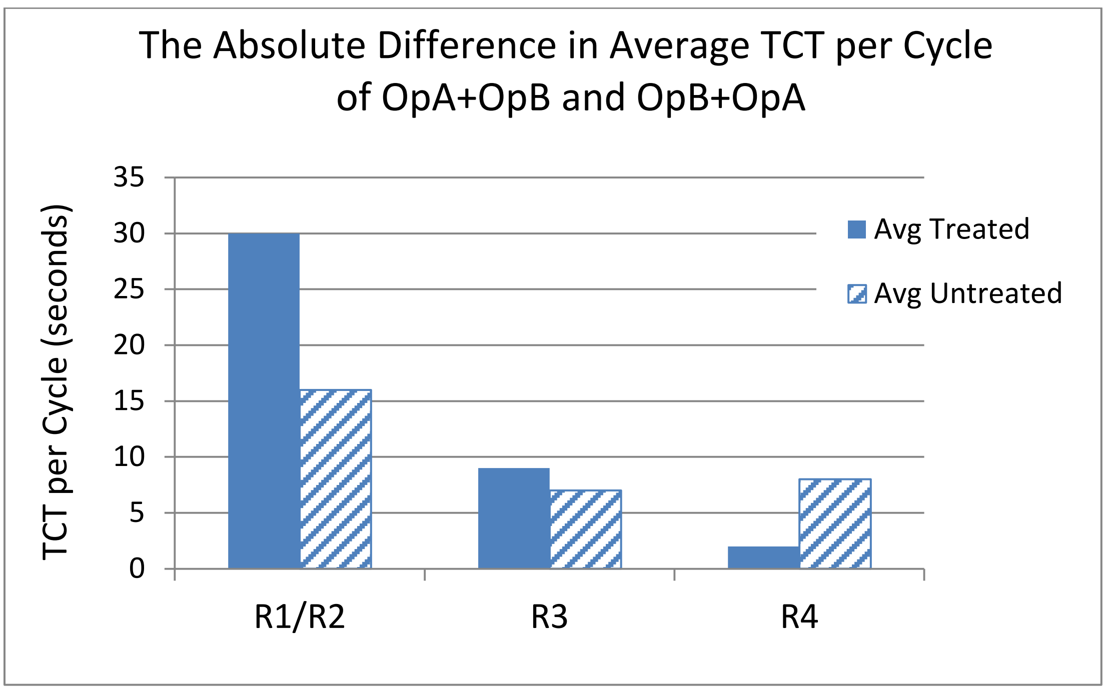


Figure 5.36. The difference in average TCT per cycle based on operator position for treated versus untreated teams in R1/R2, R3 and R4.

5.5.3. Total Throughput Time (TPT) CT Analysis

In addition to using the individual CT data from each Station to obtain the TCT, the total time for each 16-cycle segment between assessments was also recorded. Dividing the time to complete each segment by the number of cycles in them (16) results in the average total throughput time (TPT) per cycle for each Station individually. Multiplying by 2 gives the average time or TPT for both Stations combined including WT. The resulting TPT data is presented in Table 5.35. Notice the data is separated by team, run and operator order in the same manner as the TCT data in Table 5.33. The TPT data in this sub-section is analyzed in the same manner as the TCT data in the previous sub-section. The average data presented in Table 5.35 was used to create the chart presented in Figure 5.37. This figure shows similar trends as previously seen from TCT data in Figure 5.34. One difference between the TCT and TPT data is the magnitude of the TPT, especially for R1/R2, which is due to the inclusion of WT in the TPT data. Otherwise, both figures (5.35 and 5.37) show continuously decreasing operator order differences for the treated group, while the untreated group appears to level off after R3. The difference in the TPT based on treatment conditions is clearly illustrated in Figure 5.37. The difference in TPT cycle time goes from 11 seconds in R1 and R2 to 13 in R3 and finally to 17 seconds for R4. As was done for the TCT data, the TPT data can also be used to determine the effects of treatment due to operator order as seen in Figure 5.38.

Table 5.35. Average total throughput time (TPT) per cycle per individual Station for R1, R2, R3 and R4 with WT obtained from 16-cycle segment data.

Average TPT (seconds) per Cycle per Individual Stations					
	R1	R2	Avg R1+R2	R3	R4
T1					
Operator A+Operator B	126		126	104	93
Operator B+Operator A		192	192	121	91
T4					
Operator A+Operator B	162		162	121	94
Operator B+Operator A		130	130	109	95
Average Treated (1&4)	**142**	**162**	**154**	**114**	**94**
T2					
Operator A+Operator B	176		176	135	128
Operator B+Operator A		144	144	133	121
T3					
Operator A+Operator B	168		168	140	128
Operator B+Operator A		216	216	165	153
Average Untreated (2&3)	**172**	**180**	**176**	**143**	**132**

The data from Table 5.35 was used to determine the absolute difference in TPT based on operator order and is presented in Table 5.36. This data was used to create the chart in Figure 5.38 showing the absolute difference in TPT per cycle between OpA+OpB and OpB+OpA conditions. Also as expected, the trend seen in the figure is similar to that observed in Figure 5.36 for TCT.

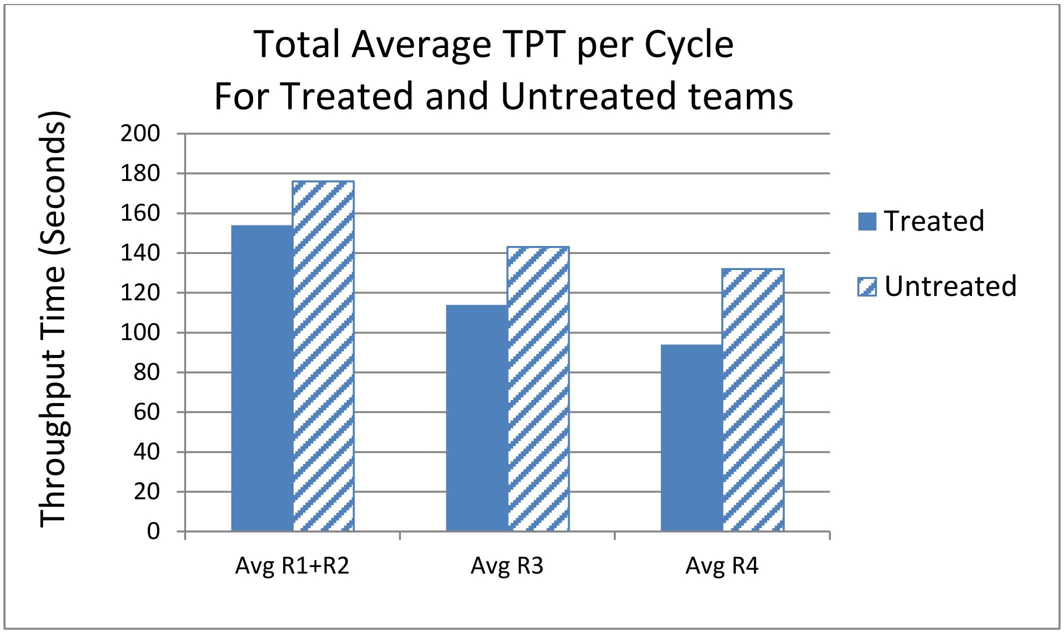


Figure 5.37. The average TPT per cycle based on both operator order conditions for treated versus untreated teams in R1/R2, R3 and R4.

Table 5.36. The absolute difference in TCT per cycle for OpA+OpB and OpB+OpA.

	The Absolute Difference TCT per Cycle in OpA+OpB and OpB+OpA		
	R1/R2	R3	R4
T1	66	17	2
T4	32	12	1
Avg Treated	**49**	**15**	**1**
T2	32	2	7
T3	48	25	25
Avg Untreated	**40**	**14**	**16**

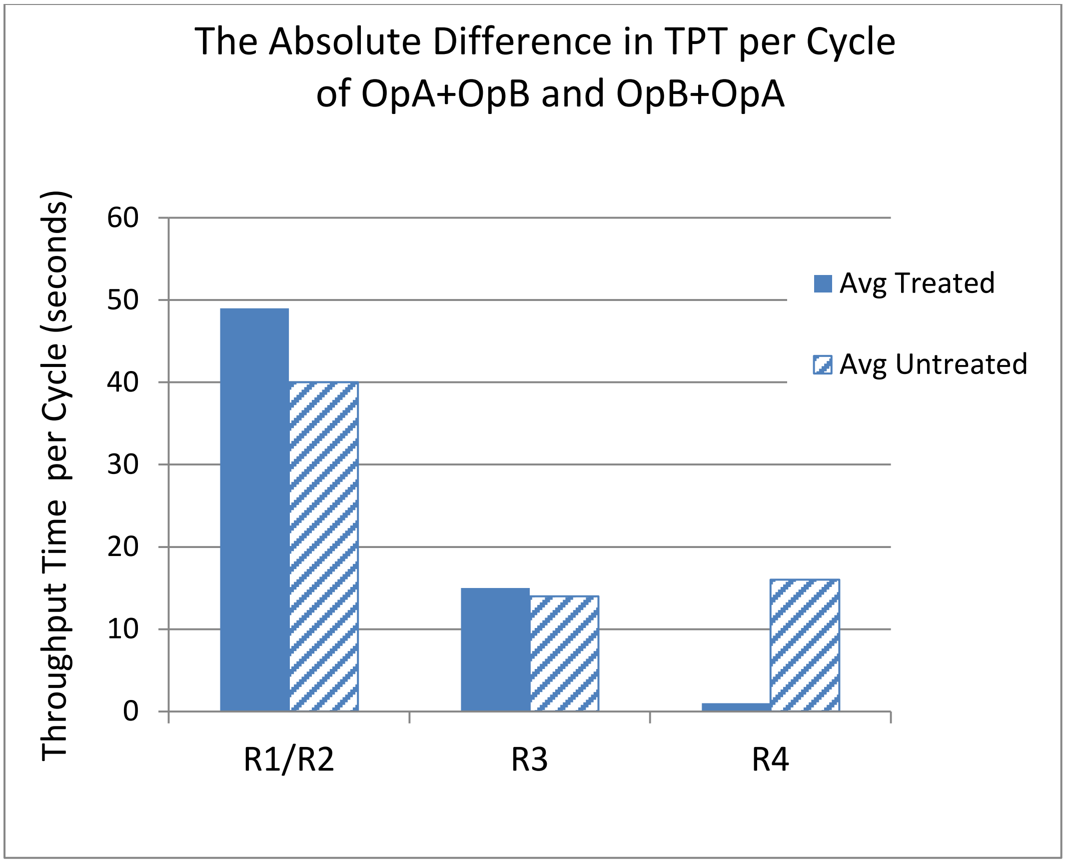


Figure 5.38. The difference in average TPT per cycle based on operator position for treated versus untreated teams in R1/R2, R3 and R4.

Figure 5.39 shows this trend in terms of percentage, illustrating the percent difference in the average TPT for the treated and untreated teams. There is a definite pattern of increasing performance disparity between the groups as each team continues through R3 and R4. This trend helps support the increasingly positive effect of systematic problem solving (2^{nd} order) compared to non-systematic (1^{st} order) problem solving illustrated in Figure 1.2 reproduced below.

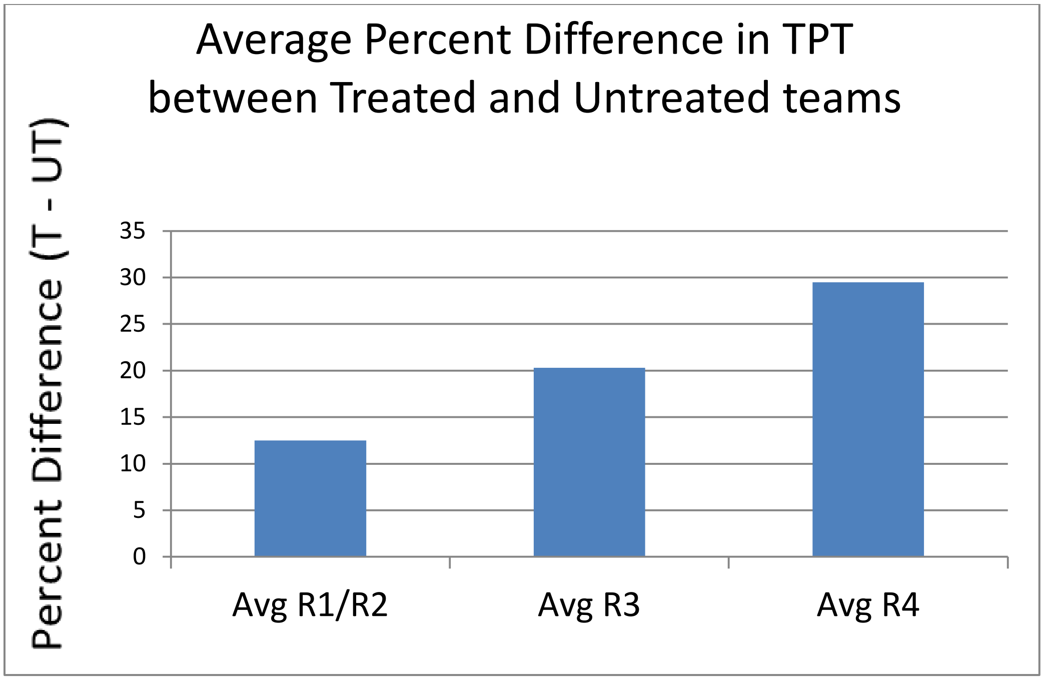


Figure 5.39. Percent difference in TPT between treated and untreated teams for R1/R2, R3 and R4.

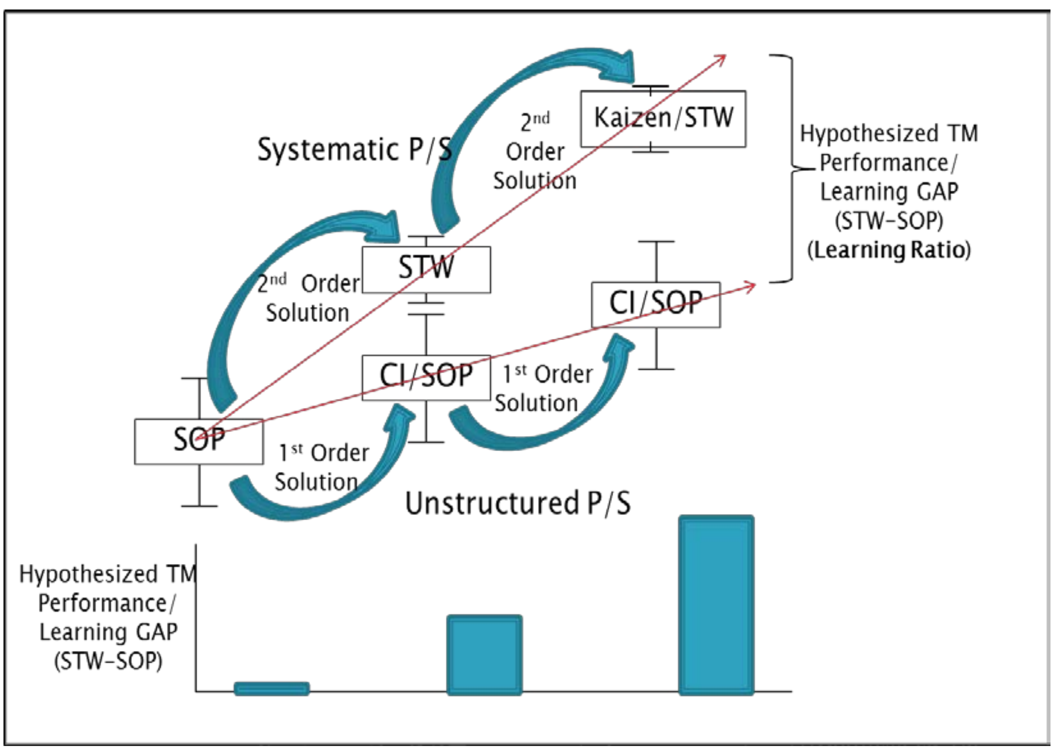


Figure 1.2**.** Conceptual illustration of part of the problem addressed in the proposed dissertation.

Finally, the TCT and TPT data for the treated and untreated teams in R1 and R2 combined (R1/R2), R3 and R4 have been combined and presented in Figure 5.40. The figure clearly shows the trend towards decreasing TCT and TPT in all conditions and a trend towards increased operator to operator consistency as the result of treatment as seen in the difference between the OpA+OpB and OpB+OpA operator order in the TCT and TPT results.

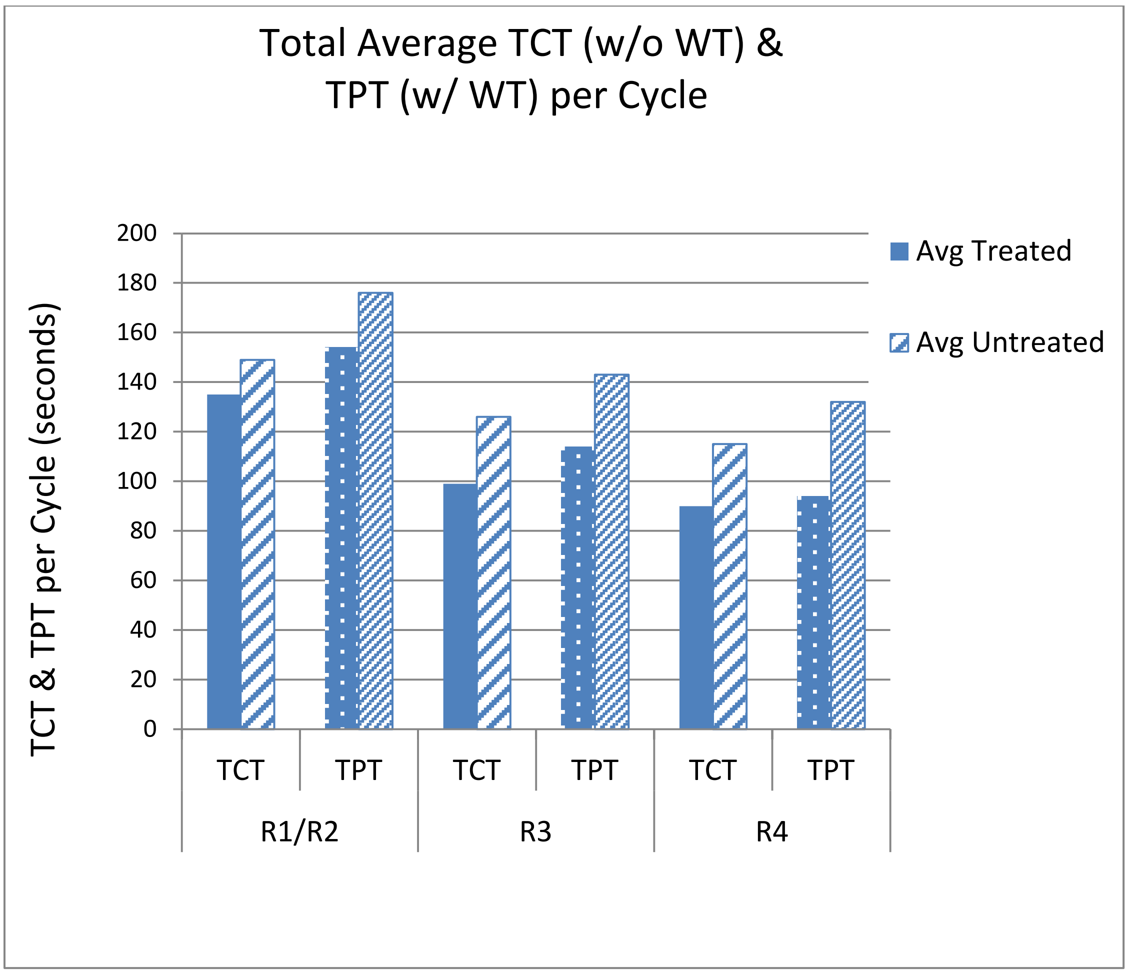


Figure 5.40. Total average cycle time (TCT) and throughput times (TPT) (including wait time) for each team and run presented in Table 5.33 and Table 5.35.

5.5.4. The Effects of Treatment on Operator Wait Time (WT)

As mentioned above, an indication of the effects of treatment on operator consistency can be seen from the difference in TCT and TPT due to operator order occurring during each run. The difference in TCT and TPT is due to WT which provides another way of observing the impact of treatment on operator performance and consistency. The smaller the WT, the more closely matched the operators performance in Station 1and 2 is. The TCT and TPT data presented in Tables 5.33 and 5.35 respectivly, was used to calculate the WT per cycle. The results are listed in Table 5.37 and graphically illustrated in Figure 5.41 The results indicate there is a high amount of TPT variation between the teams of the same group and between the operator order of each team in both groups, especially in R1/R2. Figure 5.41 also shows that by R4 for the treated group, there is very little difference in WT based on operator order or individual team compared to the R4 results of the untreated teams. While the WT varied from 3 to 4 seconds for the treated teams, the WT of the untreated teams varies from 10 to 24 seconds, a 3 to 6-fold difference from the treated R4 WT.

Table 5.37. Average WT per cycle per individual station.

Average WT (seconds) per Cycle per Individual Stations					
	R1	R2	Avg R1+R2	R3	R4
T1					
OpA+OpB	4		4	6	4
OpB+OpA		42	42	29	4
T4					
OpA+OpB	14		14	12	4
OpB+OpA		23	23	11	3
Average Treated (1&4)	**7**	**28**	**19**	**15**	**4**
T2					
OpA+OpB	38		38	19	24
OpB+OpA		19	19	21	17
T3					
OpA+OpB	9		9	7	10
OpB+OpA		38	38	22	21
Average Untreated (2&3)	**23**	**28**	**25**	**17**	**17**

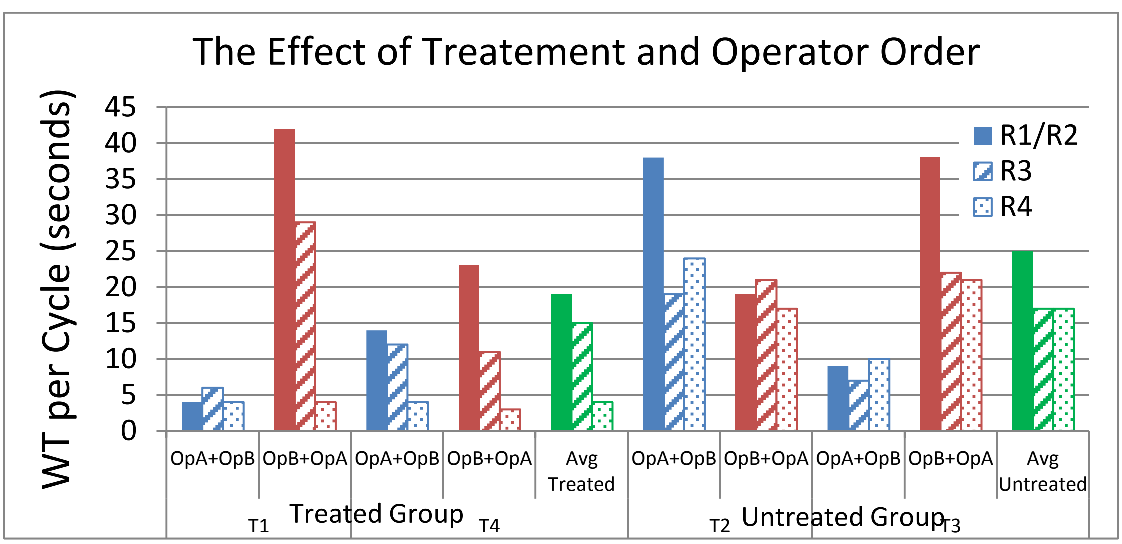


Figure 5.41. Average WT per team for OpA+OpB and OpB+OpA.

Since WT directly affects productivity, it is important to get as clear a view as possible of the differences in productivity between the treated and untreated teams. One way to see the variation more clearly is to focus on the total average WT per cycle from both operator orders combined. The data is included as part of Table 5.37 and graphed in Figure 5.42. Even though the operator orders are combined, the figure clearly shows the trend towards a continually decreasing WT for the treated group, the amount of decrease measured for the untreated group decreases from R1/R2 to R3, but levels off from R3 to R4, a similar result to that seen in the TCT analysis.

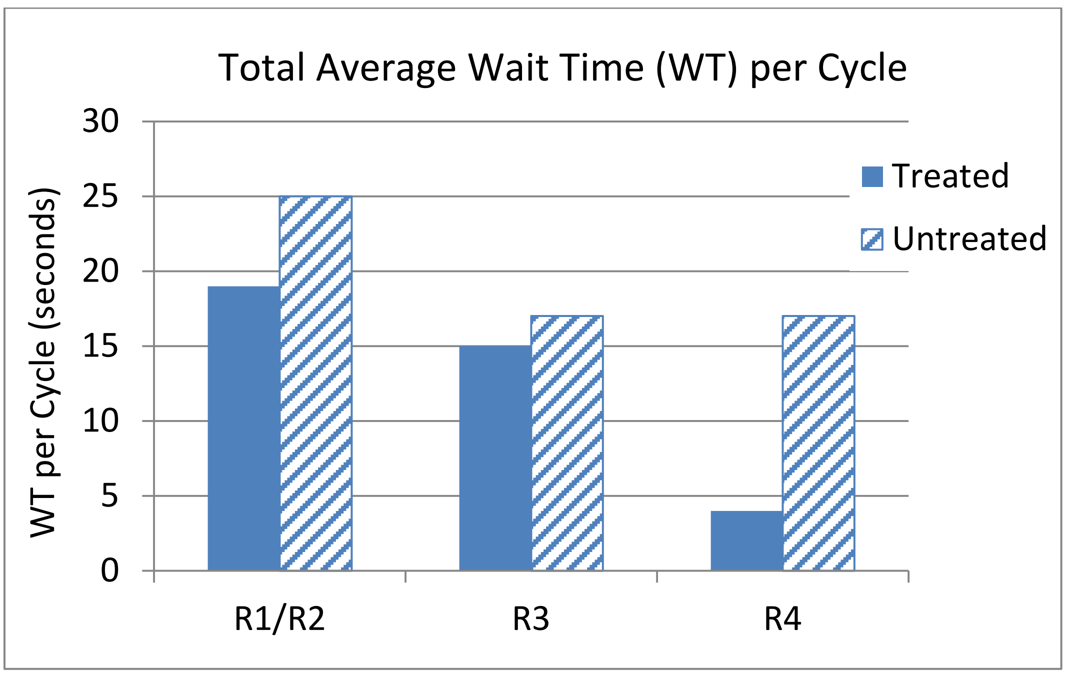


Figure 5.42. The average WT determined from the TCT and TPT values presented in Table 5.33 and 5.35.

This is perhaps more clearly illustrated in terms of percentage in Figure 5.43 showing the percent average decrease in WT for treated and untreated teams. The chart shows changes in the average percentage of WT as each group progress through all four runs.

Figure 5.43 clearly shows the amount of WT in R1/R2 is greatest for the untreated teams, but it also decreases more rapidly going form R1/R2 to R3 than for their treated counterparts. The percentage of WT change from R1/R2 to R3 is much greater for the untreated teams. However, going from R3 to R4 the percent WT decrease of the untreated teams reduces sharply, while the percent of WT decrease for the treated group increases from about 20% in going from R1/R2 to R3, to over 65% from R3 to R4. At the same time the untreated percent WT decrease from about 45% in R1/R2 to R3 too less than 20% going from R3 to R4. The overall percent decrease in WT from the base runs (R1/R2) to the end of R4 varied from about 75% to 35% (an approximately 50% variance) for treated versus untreated teams respectively. The figure also clearly shows the trend towards continually decreasing WT occurring with the treated teams while the WT for untreated teams actually increases slightly (see Figure 5.42).

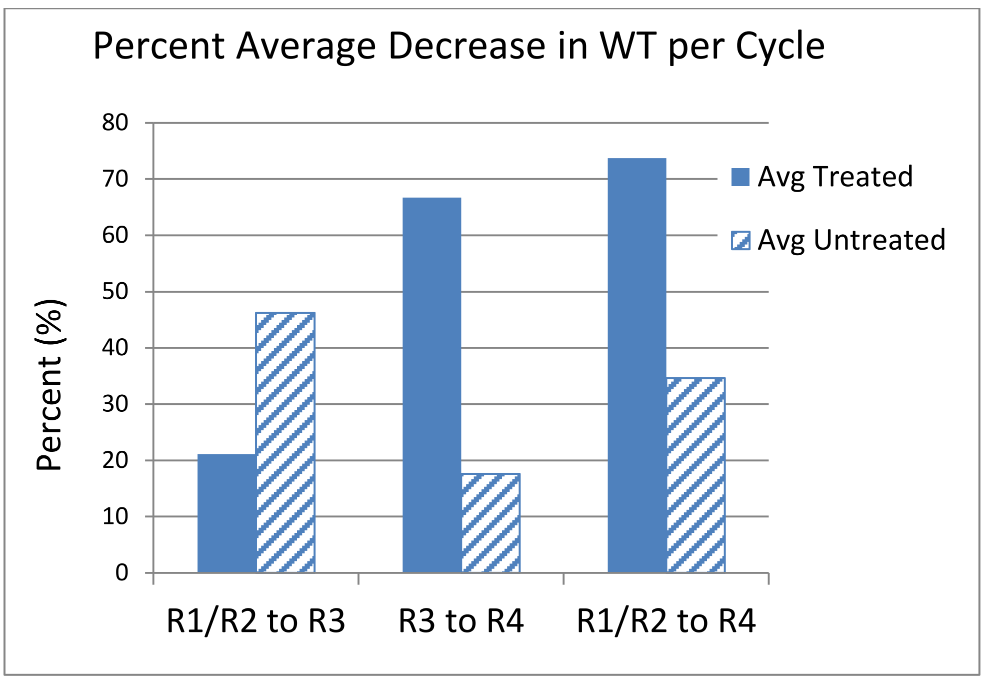


Figure 5.43. The percent average decrease in WT for treated and untreated teams.

5.5.5. Statistical Analysis of Total Cycle Time (TCT) Cycle Time Results

To determine if the results presented above are statistical ly significant two-sampled and paired t-tests were performed comparing the treated and untreated TCT results. As previously mentioned, the TCT results presented in Table 5.33 were obtained by summing the average 8-cycle data for each Station. As a result, the TCT does not include wait time (WT) between Stations. The data presented in Tables 5.33 and 5.35 were be used for the TCT and TPT analysis respectively. The complete results of the t-tests are presented in Appendix Y. The results presented in Table 5.38 come from data which in the case of the R1/R2 analysis, contains both OpA+OpB and OpB+OpA TCT data since there was no job rotation in R1 and R2. The two runs are combined because together they both represent the baseline conditions and provide 4 data points for the evaluation. Because each operator rotates once during R3and R4, there are twice as many data points for each condition, which allows the input data for the t-test analysis to be divided into both operator order conditions if the data from R3 and R4 are combined as presented. The two-sample t-test results for the TCT baseline condition, R1+R2 presented in Table 5.38 shows, as expected, there is no difference in the treated and untreated means of the total cycle time (TCT) data from R1 and R2 combined. However, as seen in the table, there is a significant difference between the TCT data of the treated and untreated teams in combined R3 and R4 results. According to the results in Table 5.38, both treated operator orders resulted in significantly different results that the untreated conditions.

Table 5.38. Two-sample t-test results for TCT data from OpA+OpB and OpB+OpA conditions.

R1 + R2 TCT CT Data		R3 + R4 TCT CT Data		
Treated vs Untreated teams		Treated vs Untreated teams		
	OpA+OpB& Operator B+Operator A		Operator A+Operator B	Operator B+Operator A
	4		4	4
T-Stat	-1.087	T-Stat	-2.819	-3.391
T-Critical (2-tail)	2.45	T-Critical (2-tail)	2.45	2.45
P-value (2-tailed)	0.319	P-value (2-tailed)	**0.030**	**0.015**

By combining the operator orders (OpA+OpB and OpB+OpA) it is possible to evaluate the TCT results of R3 and R4 individually. By matching the data sets to specific operator order, it is possible to see the progressive effect of treatment using the paired t-test. Table 5.39 shows the results of paired t-test analysis comparing the effects of treatment on R3 and R4 separately. As the summarized results show, there is a significant difference in the TCT data for both the treated and untreated teams going from R1/R2 to R3, R3 to R4 and from R1/R2 to R4. Based on these results, significant changes occurred in TCT results under all the experimental conditions. Meaning, regardless of treatment, there was a significant effect on the TCT results as the teams progressed from the base runs (R1 & R2) through R3 and R4.

To explore the effect of treatment on CTC further, two-sample t-tests were performed to compare treated and untreated results for R3 and R4. Those results are summarized in Table 5.40 showing for both runs there was a statistically significant difference in responses.

Table 5.39. Paired t-test results for treated and untreated TCT data.

Treated TCT CT Data (OpA+OpB & OpB+OpA)			
	R1+R2 to R3	R3 to R4	R1+R2 to R4
Observations	4	4	4
T-Stat	3.993	3.048	4.814
T-Critical (2-tail)	3.183	3.183	3.183
P-value (2-tailed)	**0.028**	**0.055**	**0.017**
Untreated TCT CT Data (OpA+OpB& Operator B+Operator A)			
	R1+R2 to R3	R3 to R4	R1+R2 to R4
Observations	4	4	4
T-Stat	5.258	6.810	6.241
T-Critical (2-tail)	3.183	3.183	3.183
P-value (2-tailed)	**0.013**	**0.006**	**0.008**

Table 5.40. Two-Sample t-test results from treated and untreated R3 and R4 TCT data.

TCT CT Data		
	Treated vs Untreated teams	
	R3	R4
	4	4
T-Stat	-3.308	-3.793
T-Critical (2-tail)	2.45	2.45
P-value (2-tailed)	**0.016**	**0.009**

To help clarify these results, the TCT data from R3 and R4 presented in Table 5.33 are illustrated in Figure 5.44. The chart includes the average TCT results for R1 and R2 combined R3 and R4 and clearly shows the significant changes for both treated and untreated teams, especially going from R1/R2 to R3 or R4. However, although there is not as much difference seen between R3 and R4 results, especially for treated data, in Figure 5.44, comparing each individual team results from one run to the next using the paired t-test shows significant changes even for untreated R3 and R4 data. Figure 5.45 shows the difference in CTC data based on the results illustrated in Figure 5.44. Although both treated and untreated teams exhibited significant changes in R3 and R4, as seen in Figure 5.45, there are also significant differences in the data between treated and untreated teams for R3 and R4 individually. For decrease in treated TCT results for all four runs is over 60 seconds greater than for the untreated team results over the same amount of cycles.

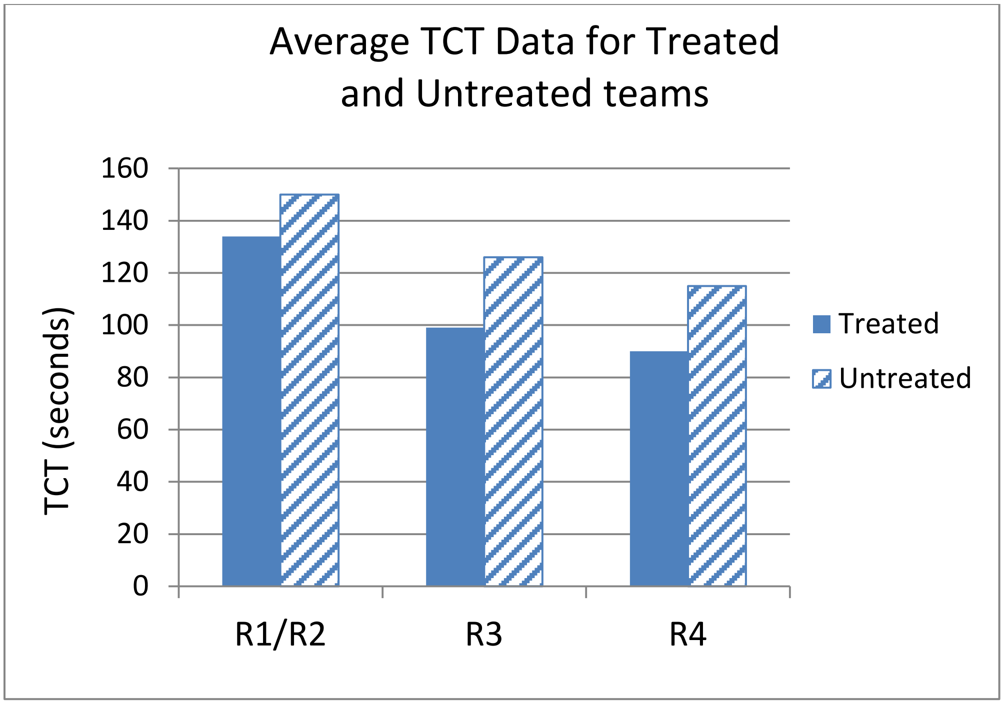


Figure 5.44. Average TCT data for treated and untreated teams.

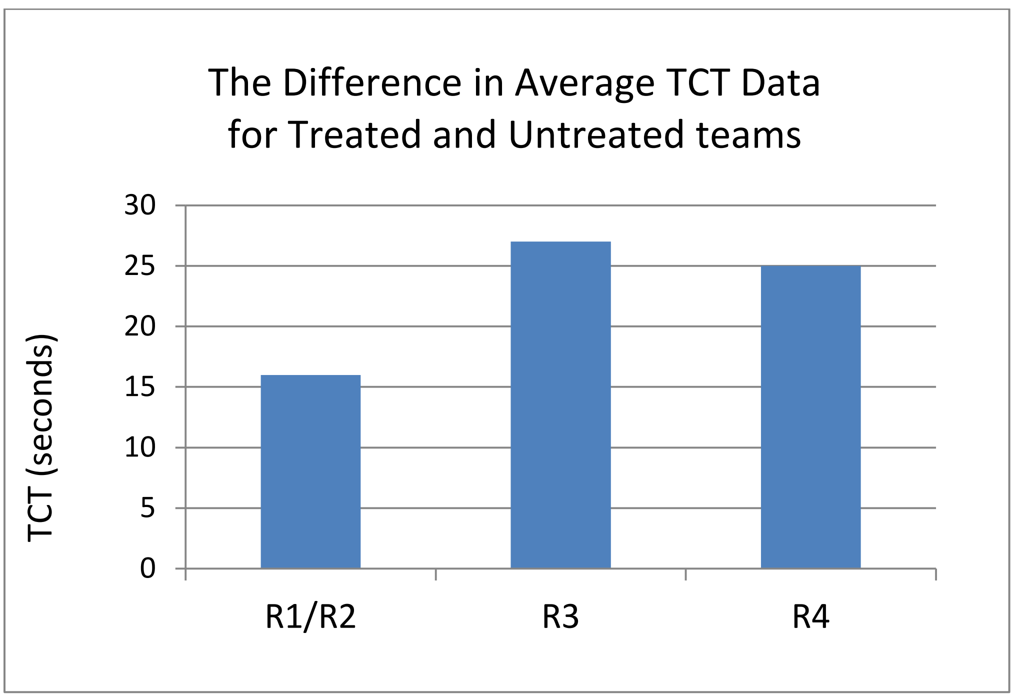


Figure 5.45. The difference in average untreated and treated TCT data from R1/R2, R3 and R4.

5.5.6. Statistical Analysis of Total Throughput Time (TPT) Cycle Time Results

As discussed in sub-section 5.5.3, the TPT results for each run were obtained by averaging the time it took to perform all sixteen 16-cycle segments combined, then dividing them by 8 to get the average TPT per cycle or unit made for that run. The most important difference between the TCT and TPT is that since the total time spent to complete a 16-cycle segment concludes when both operators are done, it includes all the WT which occurred during that period. Therefore the TPT includes WT per cycle along with time spent performing work. As previously discussed, the average WT per cycle for each assessment period is obtained by subtracting the TCT from the TPT. In this sub-section statistical analysis will be performed on the results presented in Table 5.35 to determine the significance of the TPT response to treatment. As in the previous sub-section (5.4.2.1), the analysis consists primarily of two-sample and paired t-tests. The complete results of the analysis are presented in Appendix Z.

As a consequence of how the TPT was determined it is not possible to separate out data from individual operators and stations or by operator order. Therefore, unlike the TCT data sets which contained 4 data points for R3 and R4 (due to job rotation), the TPT data sets only contain 2 data points per run per group. As a result, statistical analysis will only be performed on combined data sets from R3+R4 as well as R1+R2 (same as for TCT data analysis).

Similarly to the previous sub-section, the TPT data was analyzed using the two-sample t-test to determine if there was a significant response due to treatment for R1+R2 and R3+R4. Unlike the previous sub-section however, it was not possible to drill down deeper into the data to evaluate the difference between the OpA+OpB and OpB+OpA responses. The results of the two-sample t-tests are summarized in the Table 5.41. As expected the results of the analysis are similar to those obtained using the TCT data (Table 5.40). In particular, there is no significant difference between the treated and untreated team data for R1/R2 and a significant difference between the responses of the two groups for the R3+R4 TPT data, indicating the treatment had a significant effect on the TPT and WT.

Table 5.41. Two-sample t-test results for total throughput time (TPT) data.

TPT CT Data		
Treated vs Untreated teams		
	R1 + R2	R3 + R4
Observations	4	4
T-Stat	-1.093	-4.012
T-Critical (2-tail)	2.45	2.45
P-value (2-tailed)	0.316	**0.007**

The average TPT data shown in Table 5.35 is charted in Figure 5.46 and shows how the TPT CT responses change from R1/R2 to R3+R4. The TPT results for R3 and R4 separately are presented in Figure 5.47. The charts show a distinct trend towards lower TPT for both treated and untreated teams, as was found for the TCT data in the previous sub-section and the changes associated with treatment appear to be greater than those from untreated teams in R3 and R4. Figure 5.48 illustrates this result more clearly by showing the difference in TPT CT between the treated and untreated groups. The results illustrated in Figure 5.48a are seen in terms of percentage in Figure 5.48b which shows the difference in TPT CT improvement between the treated and untreated teams increases from about 10% in the baseline to nearly 20% after R3 and finally up to almost 30% in R4. Comparing the chart presented in Figure 5.48a with Figure 5.45 for comparable TCT data, the difference in WT (the major difference between TCT and TPT is the inclusion of WT in TPT) due to treatment continues to increase from R3 to R4 while the difference in TCT for the same runs shows a slight drop off. This result indicates an increasing disparity or imbalance in the work content of both stations due to lack of treatment, or alternately, increased synchronization between the stations as a result of treatment.

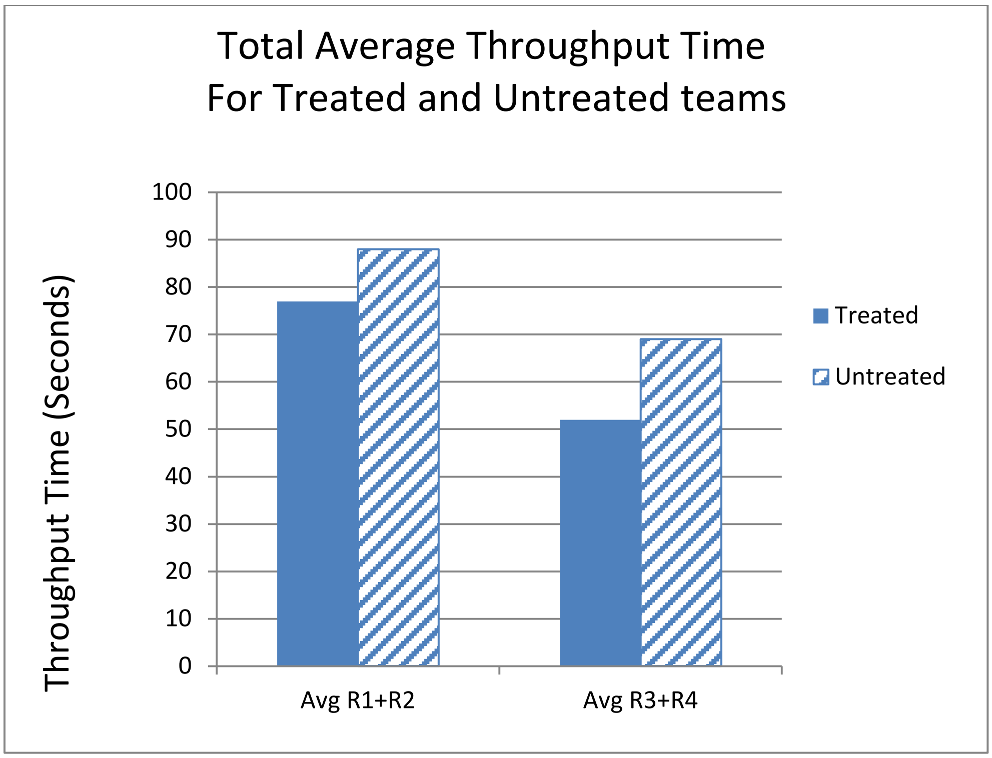


Figure 5.46. Combined R1/R2 and R3/R4 TPT response for treated and untreated teams.

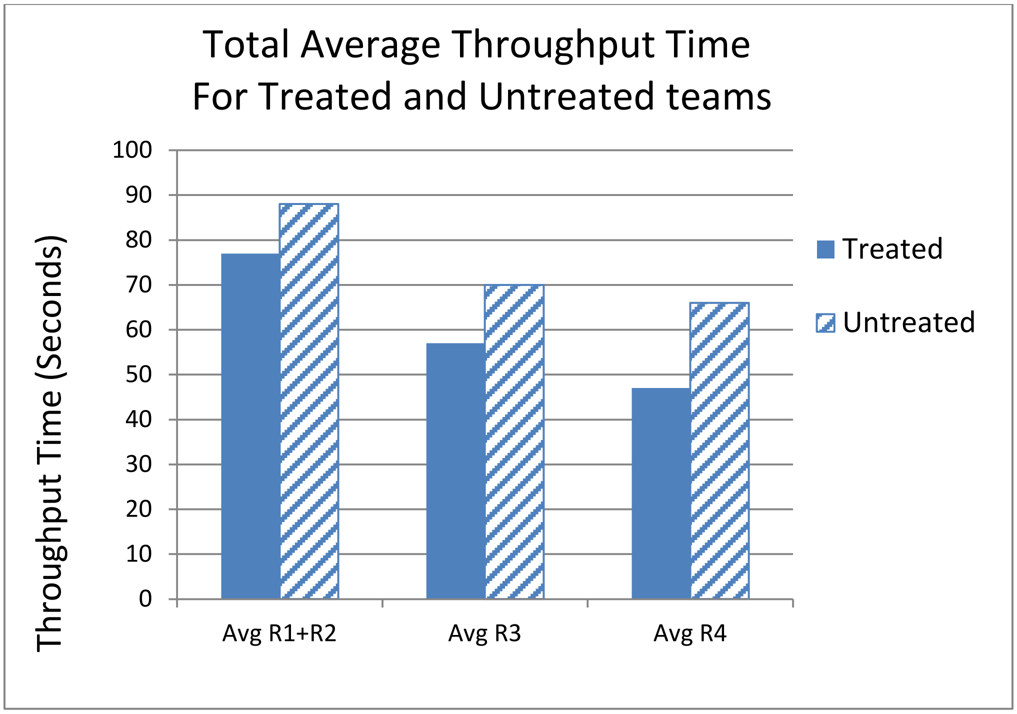


Figure 5.47. Average TPT data for treated and untreated teams.

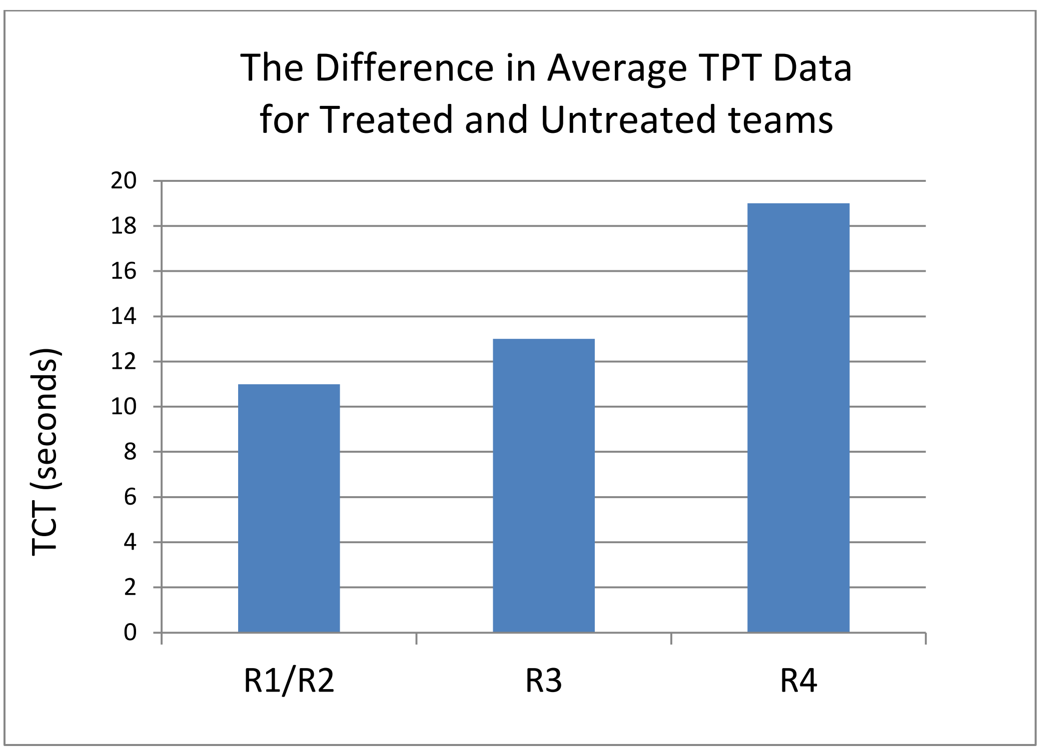


Figure 5.48a. The difference in average untreated and treated TPT data from R1/R2, R3 and R4.

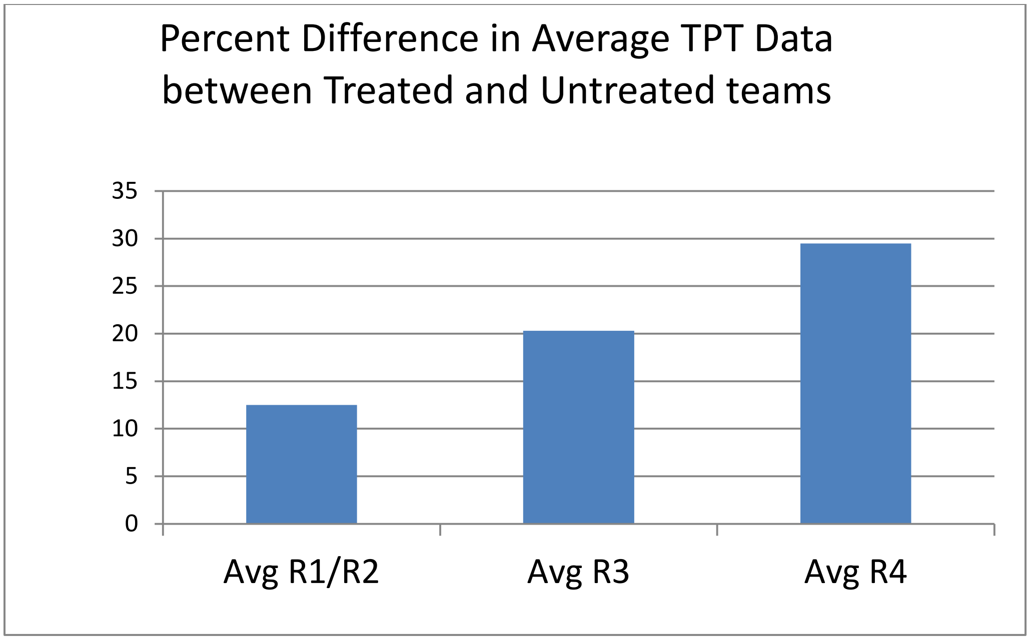


Figure 5.48b. The percent difference in average TPT between treated and untreated teams.

5.5.7. Learning Curve Coefficient (LCC) Analysis of TPT Learning Curves

Individual and contextual LCs introduced and discussed in previous sections provides a clear indication of the learning and performance for individual operators. However, only TPT LCC analysis can provide information on the effects of treatment on the aggregated system learning rates. Because the TCT results are constructed using individual CT data and do not include WT, they also give limited information on the total system performance. Although the TCT results help support the validity of observable trends, without including WT, they are not the primary source for system performance. Therefore only the LCs based on TPT will be considered for statistical analysis.

As mentioned earlier, the TPT LCs were constructed using the 16-cycle TPT results from each team. To match the TPT LCC data sets with the CT data used in the previous TCT and TPT CT related sub-sections the complete LCs will be used in the analysis. This means all 256 cycles of each run will be included in the statistical analysis instead of just partial runs. This will allow direct correlation with the TPT CT results. Also, since the TPT data consists of 16 cycles instead of the 8 cycles used in the individual and contextual analysis, the data is inherently more stable. The complete set of LCs is presented in Appendix AA. An unfortunate consequence of using this methodology is that it precludes the possibility of direct comparison of the TPT LCC results with the earlier individual and contextual results. Figures 5.48 to 5.51 show examples of R1, R2, R3 and R4 TP T LCs. The TPT LCs are very similar to the individual LCs discussed earlier. Like the previous LCs, the TPT LC figures also show the power law equation along with the LCC as part of the equation. Notice the differences in slope and the LCCs (exponents) in the equations. The LCs for R1 and R2 are similar and exhibit steeper slopes and therefore higher LCCs because they are both from inexperienced operators, while for R3 and R4 the slopes of the LCs are less pronounced and possess lower LCCs, more indicative of experienced operators TCT and TPT discussed previously. No cycles were excluded from the analysis since there are only a total of 16 cycles per run.

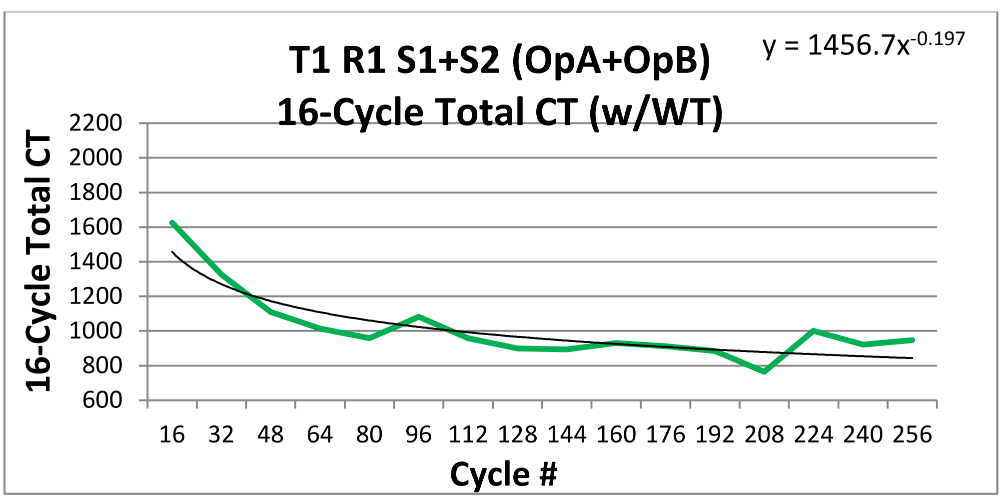


Figure 5.49. TPT LC for team 1, R1, Operator A at Station 1 and Operator B at Station 2.

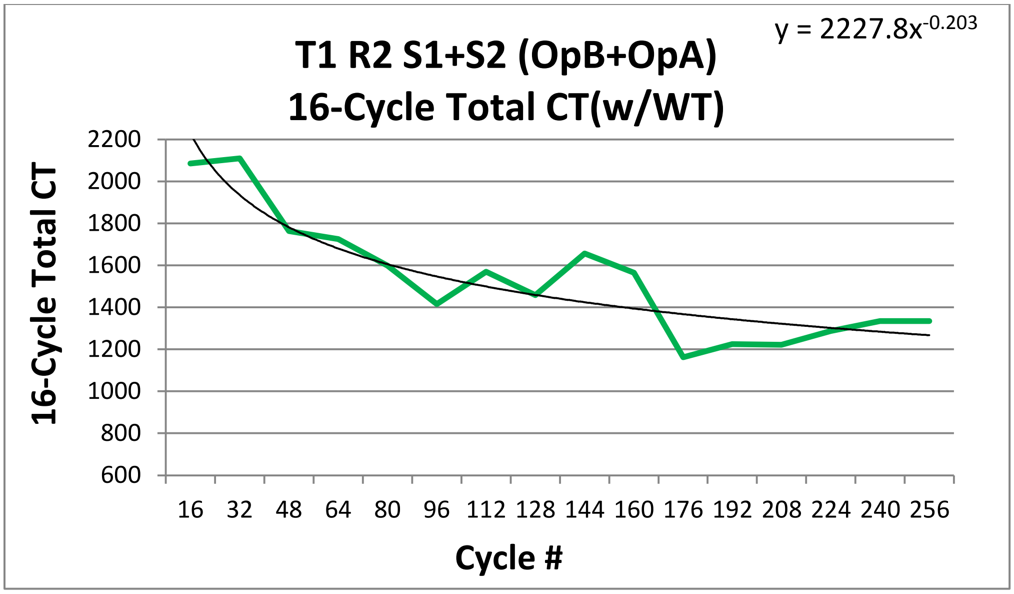


Figure 5.50. TPT LC for team 1, R2, Operator A at Station 1and Operator B at Station 2.

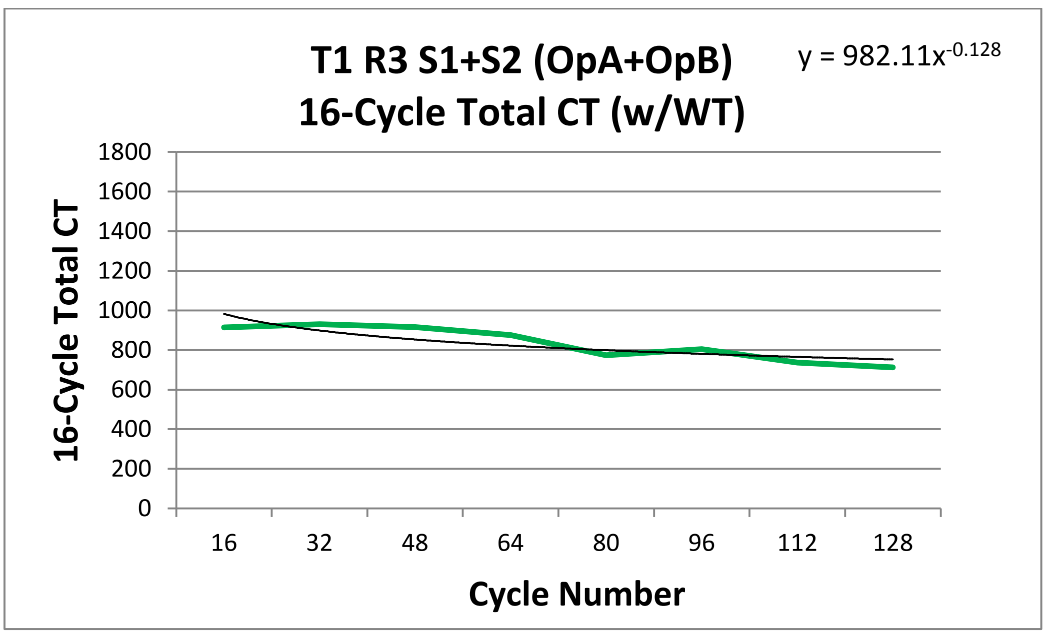


Figure 5.51. TPT LC for team 1, R3, Operator A at Station 1 and Operator B at Station 2.

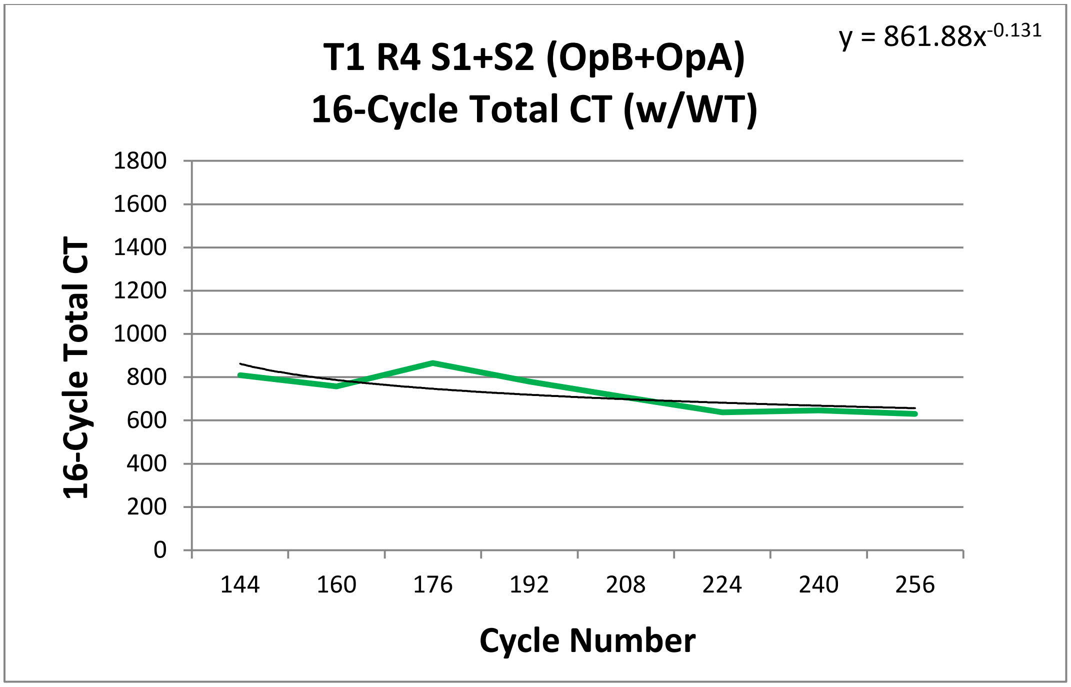


Figure 5.52. TPT for team 1, R4, Operator A at Station 2 and Operator B at Station 1.

The LCCs from each curve are presented in Table 5.42. As in the TPT CT data, the TPT LCCs can be broken down based on operator order but not by specific single operator or Station. Figure 5.53 shows a chart of the data presented in Table 5.42. As seen in the figure, there is a wide range of responses, but as noted earlier, the R1/R2 LCCs are highest in nearly all conditions. In R3 and R4 the LCC response was more mixed although it appears the responses were somewhat similar based on operator order. For untreated teams the R3 LCCs were greater or equal to their R4 LCCs. As mentioned, the R3 and R4 LCCs of both groups varied more by operator order than for R1/R2. For untreated teams, the R3 LCCs for OpA+OpB was approximately equal to their R4 response while for OpB+OpA the R3 LCCs were much greater than their R4 LCCs.

Table 5.42. LCC results for total throughput time (TPT) including wait time for R1, R2, R3 and R4.

	R1	R2	R3	R4
T1				
OpA+OpB	-0.197		-0.128	-0.028
OpB+OpA		-0.203	-0.057	-0.131
T4				
OpA+OpB	-0.144		-0.202	-0.097
OpB+OpA		-0.115	-0.077	-0.093
Avg Treated	-0.171	-0.159	-0.116	-0.087
T2				
OpA+OpB	-0.17		-0.06	-0.06
OpB+OpA		-0.055	-0.077	0.019
T3				
OpA+OpB	-0.21		-0.088	-0.074
OpB+OpA		-0.12	-0.118	0.0057
Avg Untreated	-0.190	-0.088	-0.086	-0.03

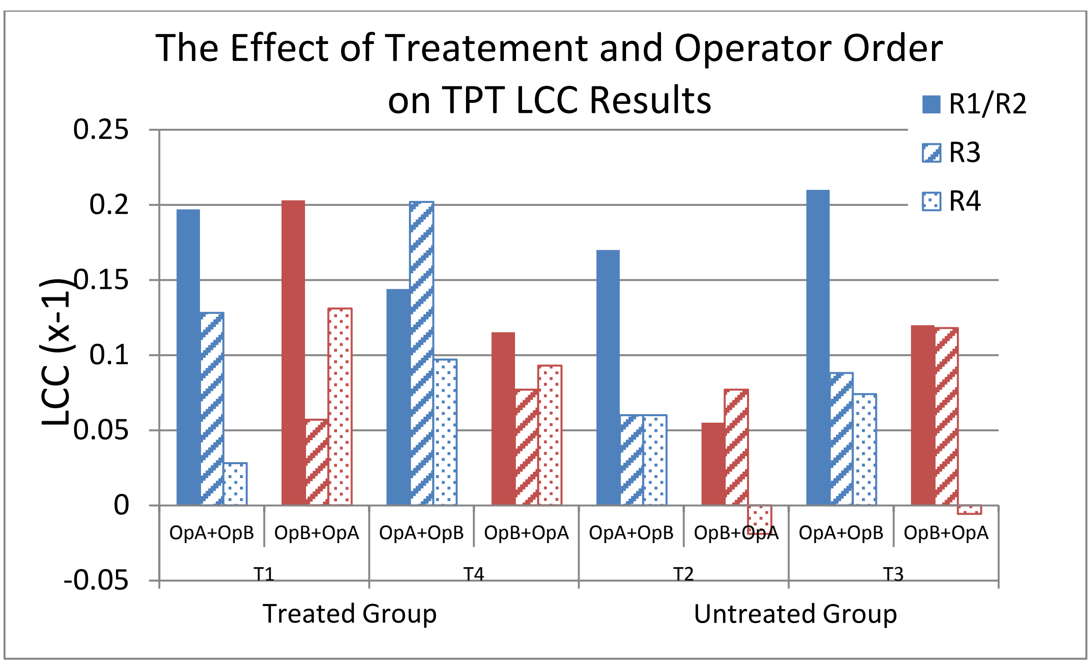


Figure 5.53. Operator order specific TPT LCCs for R1/R2, R3 and R4.

The R4 LCCs for the untreated OpB+OpA condition even exhibits negative learning, possibly due to operator burden. For treated teams the situation was also operator order dependent but the magnitude of the LCC response shifted. The R3 LCCs for OpA+OpB were greater than for the OpB+OpA condition. However, for R4 the OpB+OpA conditions resulted in LCCs that were greater than their R3 predecessors.

The impact of operator order on the LCC results seen above can be seen more clearly using averaged data presented in in Table 5.43 and illustrated in Figure 5.54. The figure shows the difference in average LCCs between the OpA+OpB and OpB+OpA conditions.   The average LCC results which are also presented in Figure 5.54 more clearly reveals a trend towards decreasing LCCs going from R1/R2 to R3 and then to R4 for both groups, however, there is a noticeable difference in the rate of decrease. In particular, the decrease in LCCs for the treated group occurs at about half the rate associated with the treated group, indicating more dynamic learning is occurring within the treated teams than within their untreated counterparts.

Finally, using the average treated and untreated TPT LCC values presented in Table 5.43 and shown in Figure 5.54, the percent difference in the average TPT LCC values were calculated and graphed in Figure 5.55.   Comparing the TPT LCC results to the TPT CT results in Figure 5.36 reveals the same trend in the gaps, which is also an expected outcome according to the model shown in Figure 1.2 which was re-introduced in the previous sub-section to illustrate the possible existence of an increasing learning gap between treated and untreated teams.

Table 5.43. Average operator order specific TPT LCCs.

	R1/R2	R3	R4
Treated			
Avg Operator A+Operator B	-0.171	-0.165	-0.063
Avg Operator B+Operator A	-0.159	-0.067	-0.112
Average Treated	**-0.165**	**-0.116**	**-0.0875**
Untreated			
Avg Operator A+Operator B	-0.19	-0.074	-0.067
Avg Operator B+Operator A	-0.088	-0.098	0.012
Average Untreated	**-0.139**	**-0.086**	**-0.0275**

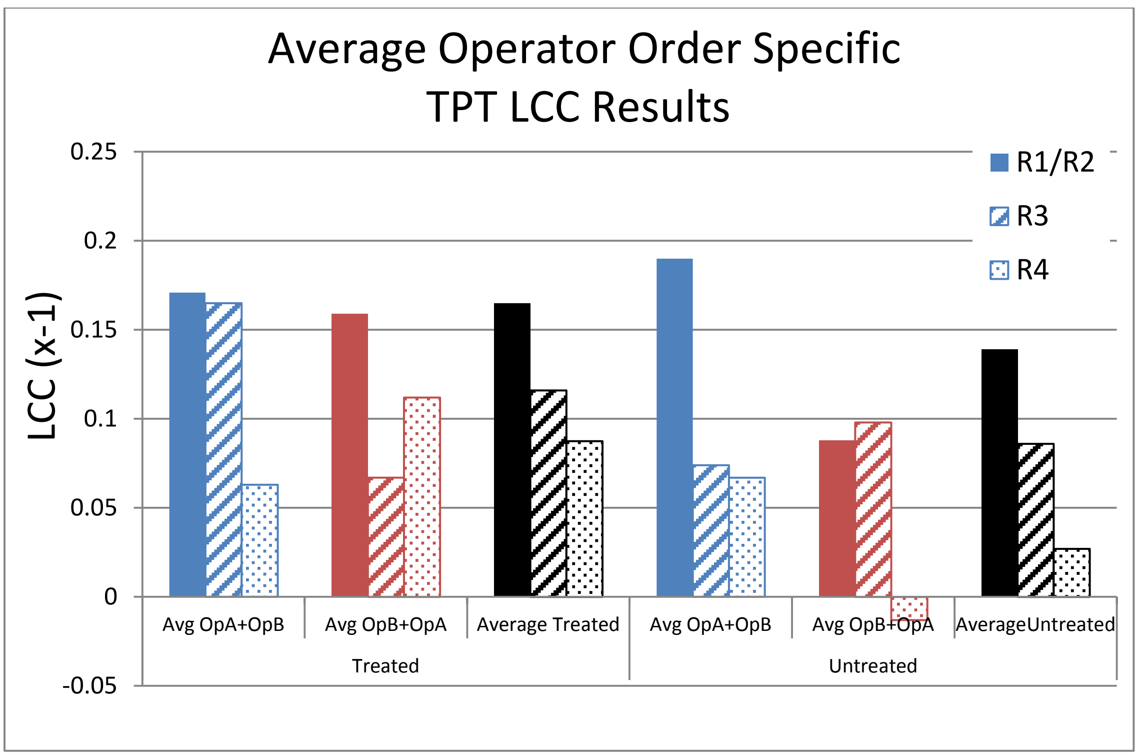


Figure 5.54. Average operator order specific LCC results for R1/R2, R3 and R4.

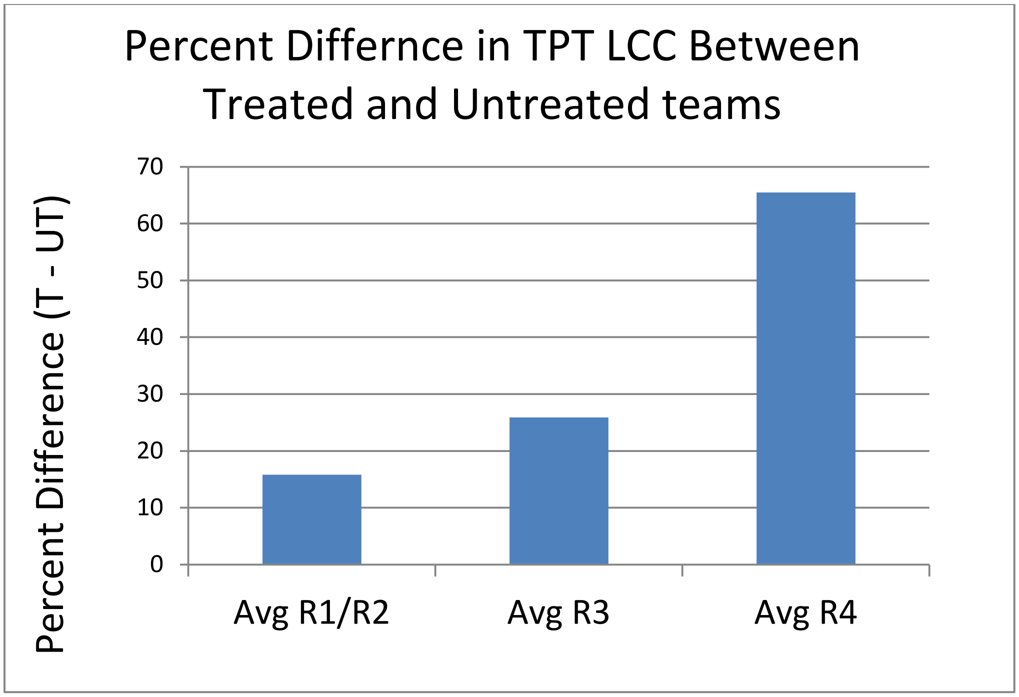


Figure 5.55. The percent difference in TPT LCC between treated and untreated teams.

5.5.8. Statistical Analysis of TPT LCC Learning Curve Results

Learning curve coefficients (LCCs) obtained from TPT LCs were statistical ly analyzed using paired and two-sample t-tests on the data in Table 5.42 in the same manner as in previous sections. The complete set of TPT LC t-test results are presented in Appendix BB.

Because the operator order specific data sets are so small (n = 2), this analysis will concentrate on evaluating the effect of treatment on combined OpA+OpB and OpB+OpA data. Statistical analysis using the two-sample t-test will examine the significance of each group's response to treatment in the combined R1/R2 runs and R3 and R4. The results will indicate if the treatment resulted in significantly different learning responses of the two groups. In addition, paired t-tests were also performed on paired data sets to evaluate the effect of treatment on paired responses as each team progressed through R1/R2 to R3 and finally to R4.

The results of the two-sample t-tests are summarized in Table 5.44. From the results, none of the responses were significantly different at the 95% level, however the R4 LCC responses are significantly different at about a 90% level (bold print). Looking at the difference based on the combined responses of R3 and R4, there is only a slight decrease in the p-value, indicating only a slight increase in significance over the individual R4 results. To understand these results it is helpful to examine the results of the average combined OpA+OpB and OpB+OpA LCC which are presented in Table 5.43and illustrated Figure 5.56. According to the two-sample t-test to determine the differences between the treated and untreated TPT LCC data seen in the figure, there is about a 90% chance the average data for R4 and R3+R4 are significantly different.

Table 5.44. Summary of two-sample t-test results of treated vs untreated TPT LCC data.

Summary of Two-Sample t-test Results from Treated vs Untreated TPT LCC Data (OpA+OpB & OpB+OpA)				
	R1+R2	R3	R4	R3+R4
Observations	4	4	4	8
T-Stat	-0.656	-0.875	-1.892	-1.808
T-Critical (2-tail)	2.45	2.45	2.45	2.145
P-value (2-tailed)	0.536	0.415	**0.107**	**0.092**

However, as seen in Figure 5.56, the difference in the treated and untreated TPT LCC results increase moving from R1/R2 to R3 and then to R4, indicating that although not statistically significant, due perhaps to the small sample size, a continual increase in the learning rate of the team members acting as operators is occurring on the treated teams.

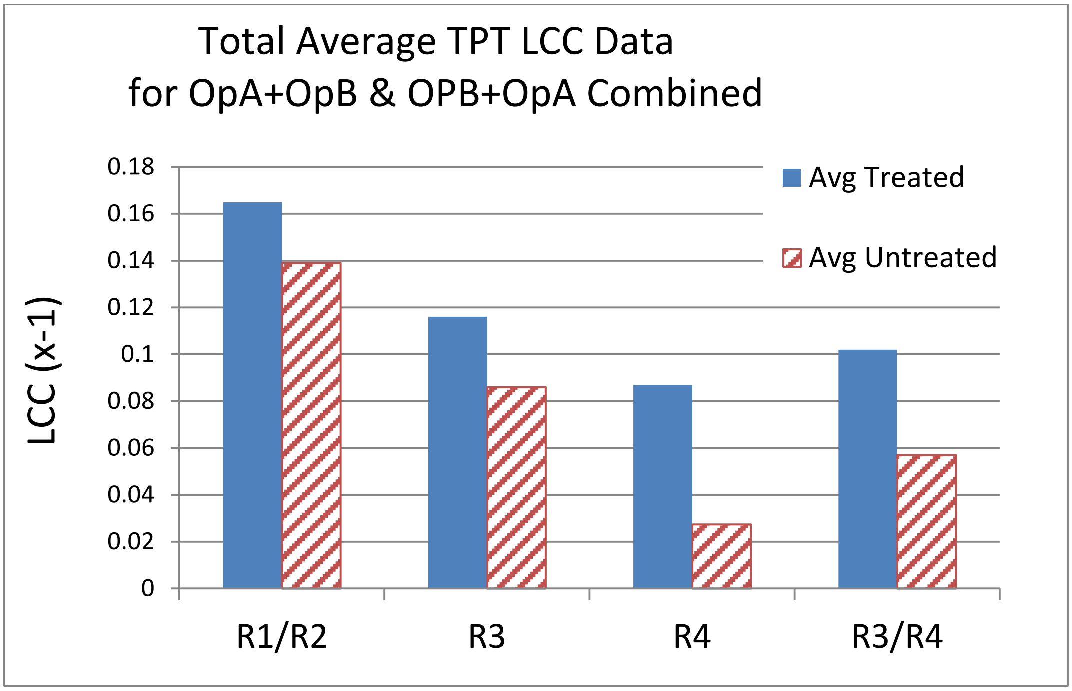


Figure 5.56. The average TPT LCC data for OpA+OpB and OpB+OpA combined.

Besides the observed differences between the treated and untreated data sets, it is important to examine the effects of treatment on each group separately. This can be accomplished using the paired t-test to evaluate matched data sets as they progress through each run or states. The results of the paired t-test analysis are summarized in Table 5.45 and show a statistically significant difference in the TPT LCC response was observed for the treated group going from R1/R2 to R3/R4 and marginally significant from R1/R2 to R3 . The amount of decrease in the TPT LCC results as each group of teams moved from one state to another (R1/R2 to R3, R3 to R4, and R1/R2 to R3/R4 is illustrated graphically in Figure 5.57. Even though only the change from R1/R2 to R3 and R1/R2 to R3/R4 was statistically significant, in each case the LCC for the untreated group decreases more than the corresponding treated group. The trend is even more clearly illustrated in Figure 5.58 which shows the difference in the amount of LCC decrease as a percentage of overall LCC going from state to state**.** This figure shows that while the learning rate (LCC) in both groups decreases about the same from R1/R2 to R3, there is a significant difference going from R3 to R4 and from R1/R2 to R4. In particular, the untreated group exhibits a drop-off in LCC of between about 70% to 80% from R3 to R4 and R1/R2 to R4 compared to a decrease of only about 25% to less than 50% for the treated group.

Table 5.45. Summary of Paired t-test results for treated and untreated TPT LCC data.

Treated TPT LCC Data (OpA+OpB & OpB+OpA)				
	R1/R2 to R3	R3 to R4	R1/R2 to R4	R1/R2 to R3/R4
Observations	4	4	4	4
T-Stat	-2.585	-0.650	-2.095	-3.255
T-Critical (2-tail)	3.182	3.182	3.182	3.182
P-value (2-tailed)	**0.081**	0.562	0.127	**0.047**
Untreated TPT LCC Data (OpA+OpB & OpB+OpA)				
	R1+R2 to R3	R3 to R4	R1+R2 to R4	R1/R2 to R3/R4
Observations	4	4	4	4
T-Stat	-1.310	-1.924	-2.191	-1.943
T-Critical (2-tail)	3.182	3.182	3.182	3.182
P-value (2-tailed)	0.282	0.150	0.116	0.147

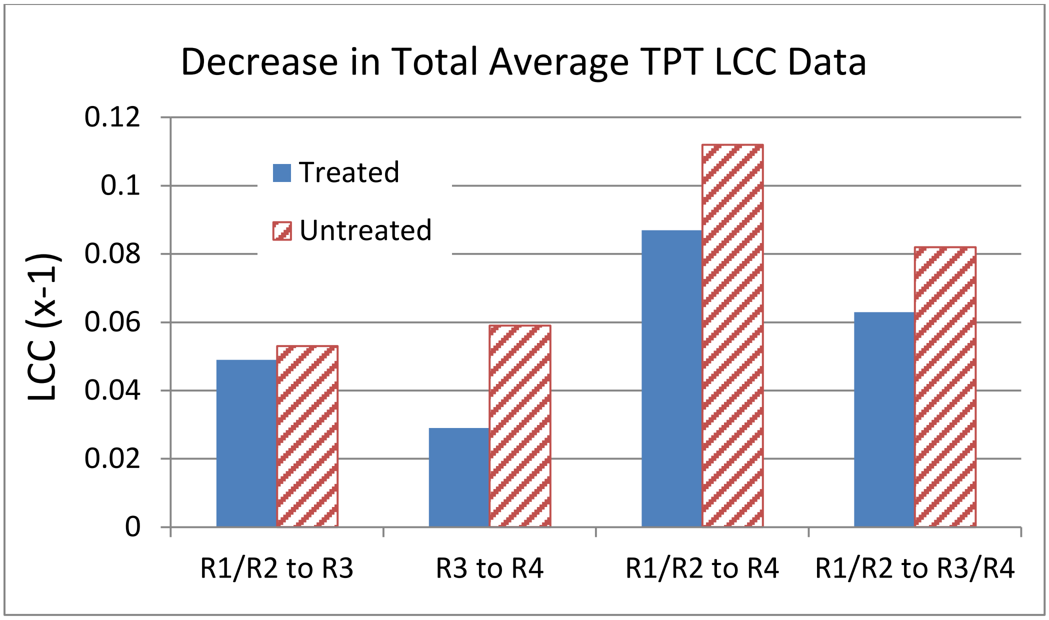


Figure 5.57. The change in total average TPT LCC data for OpA+OpB and OpB+OpA combined going from R1/R2 to R3, R3 to R4 and R1/R2 to R3/R4.

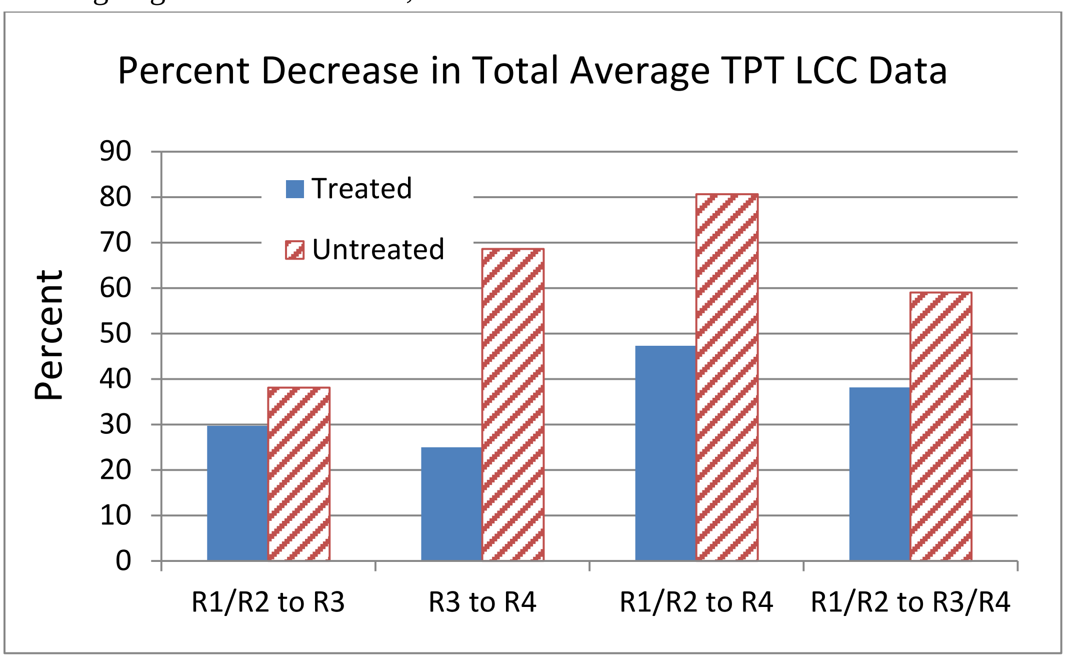


Figure 5.58. The percent decrease in TPT LCC from state to state (R1/R2 to R3, R3 to R4, R1/R2 to R4 and R1/R2 to R3/R4).

5.6 The Effect of Treatment on Defect Rates, team Member Attitude, and Physical and Mental Burden

5.6.1. Defect Rates

Other important outcomes resulting from the focus on systematic P/S and Standardization for continuous improvement and learning include its impact on quality, team member attitude, and both physical and mental burden. It is of course critical that improvement activities do not result in increased quality problems.

Defects were tracked continuously during the course of each run and reported at 16-cycle intervals. The totaled results were averaged per 16-cycle segment and are presented in Table 5.46 and graphically illustrated in Figure 5.59. As seen in the figure, the defect rate for the treated teams were relatively consistent compared to the untreated rate. While treated defects were about 2 per 16-cycle segment or set in R1 and R2, the untreated defect rate varied from over 2.5 per set down to about 0.5 defects per set in R1 and R2 respectively. In both R3 and R4 the defect rate for the untreated teams is consistently below that of the treated teams. In R3, treated teams averaged 1.3 defects per 16-cycles compared to 2.0 for the untreated teams. In R4, the defect rate decreased even more for the treated teams, down to 0.2 per 16-cyclc segment, while the untreated teams saw a decrease from 2.0 to 1.0 defect per 16-cycle segment. The combined averages of the defect rates from the baseline (R1/R2) and treated (R3/R4) runs are shown in Figure 5.60. As seen in the figure, the total average baseline defect rate per 16 cycles varied from 1.6 for the untreated teams to 2.2 defects per 16-cyces for the treated teams. While the untreated teams had few defects initially, the data shows as the teams progressed through R3 and R4 the situation changed. In both R3 and R4, the defect rate for the treated group was less than for their untreated counterparts. The results show the total average defect rate for the treated teams is reduced from 2.15 per 16-cycle segment down to 0.75 per segment or about 65% compared to almost no change for the untreated teams.

Table 5.46. Defects per 16-cycle segment for treated and untreated teams.

	Defects per 16 cycles	
	Treated	Untreated
R1	2.2	2.6
R2	2.1	0.5
Avg R1+R2	**2.2**	**1.6**
R3	1.3	2
R4	0.2	1
Avg R3+R4	**0.8**	**1.5**
% Change R1/R2 to R3/R4	-186.7	-3.3

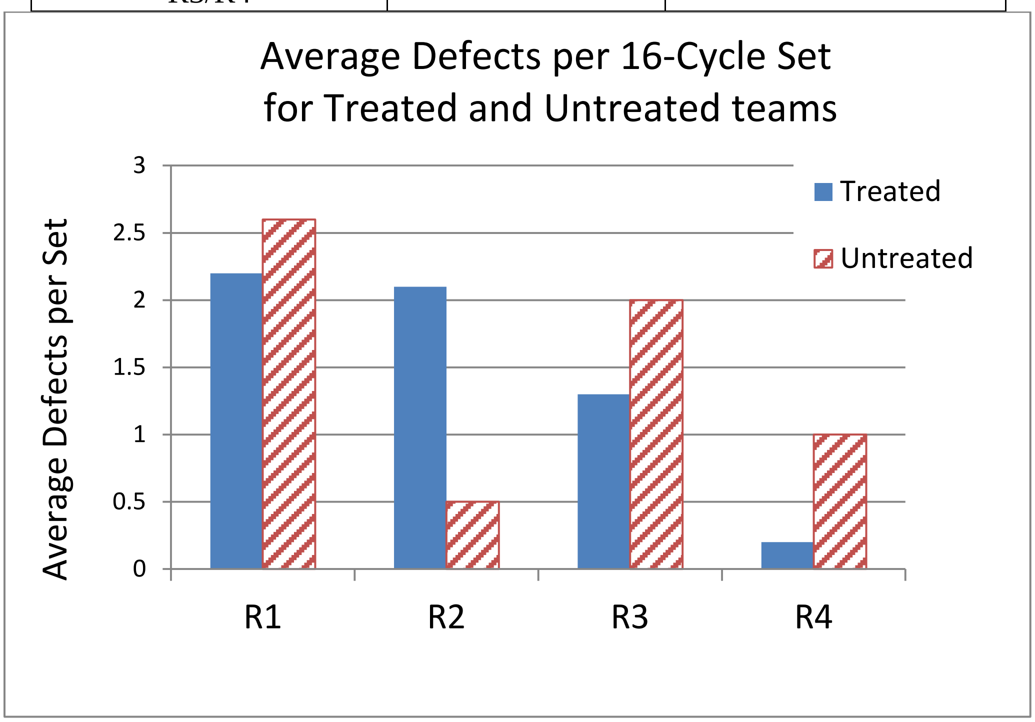


Figure 5.59. Total average defects per 16-cycle segment for treated and untreated teams.

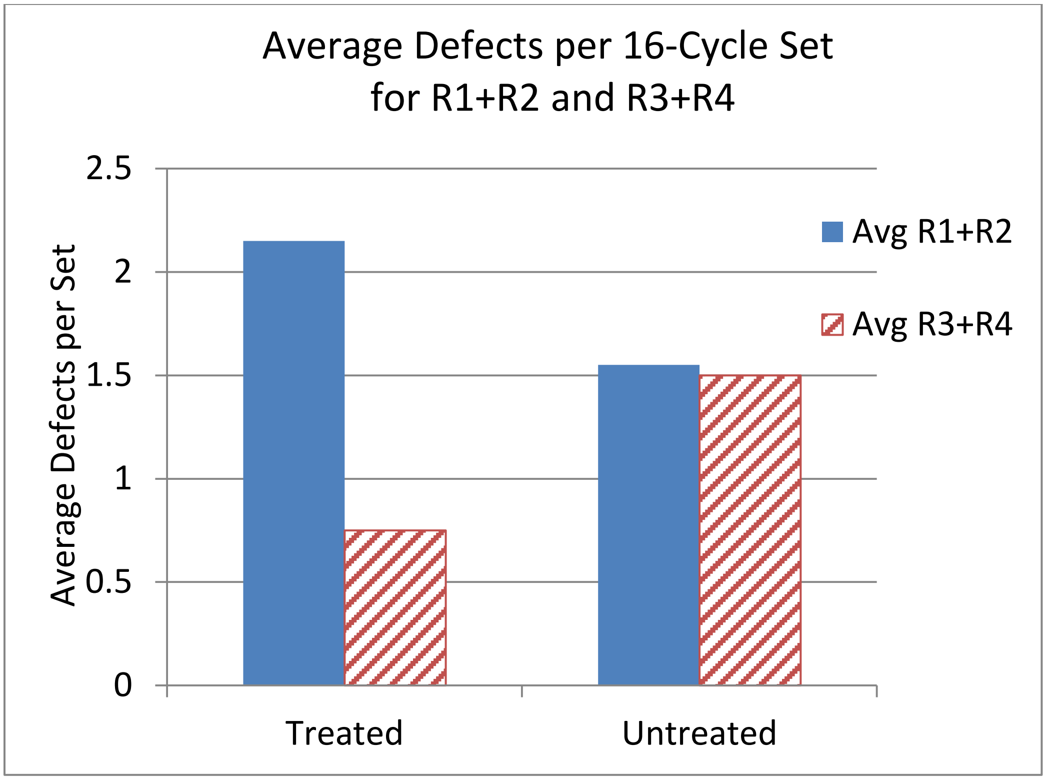


Figure 5.60. Average defect rate change for baseline (R1/R2) to treatment runs (R3/R4).

5.6.2. Team Member Attitude and Physical and Mental Burden

Also as part of this research operator (team member) attitude as well as the physical and mental burden or stress each team member experienced during each run was tracked at 16-cycle intervals. Team members were asked to rank their attitude and perceptions of mental and physical burden at the end of each 16-cycle set during the runs. Individual team Attitude was ranked on a scale of 1 to 5 with 1 being “totally bored” to 5 being “fully engaged”. Mental and physical burden was ranked on a scale of 1 to 10, with 1 being the lowest possible or least demanding or stressful condition possible and 10 being the highest, or most stressful or physically demanding level. A copy of the 16-cycle operator self-assessment sheet is presented in Appendix DD. The average of both team members responses are presented in Table 5.47. The table includes the percentage of change measured by each group for their attitudes towards doing the work, and the amount of physical and mental burden they experienced.

Table 5.47. Total average operator self-assessment results.

		Average Total Group Results				
	Attitude		Mental Burden		Physical Burden	
	Treated	Untreated	Treated	Untreated	Treated	Untreated
R1	3.5	2.4	4.3	3.8	3.8	4
R2	3.3	2.9	3.7	3.4	3	3.7
Avg R1+R2	**3.4**	**2.65**	**4**	**3.6**	**3.4**	**3.85**
R3	3.4	2.7	2.8	3.6	2.2	3.6
R4	3.8	2.8	2.8	3.9	2.8	3.9
Avg R3+R4	**3.6**	**2.75**	**2.8**	**3.75**	**2.5**	**3.75**
% Change R1/R2 to R3/R4	5.6	3.6	-42.9	4.0	-36.0	-2.7

The results presented in Table 5.47 are graphed in Figures 5.61a and 5.61b. Operator attitude for both the treated and untreated team members as seen in Figure 5.61a changed very little during the initial two baseline runs (R1 and R2). However, the overall attitude of the team members in the untreated teams is consistently lower than for their treated counterparts. Both physical and mental burden results were also somewhat different for the two groups in R1 and R2. The treated group reported slightly higher mental burden than their untreated counterpart (even though both groups performed under the same conditions), but the untreated group reported about 0.5 points (scale 1-10) higher physical burden.

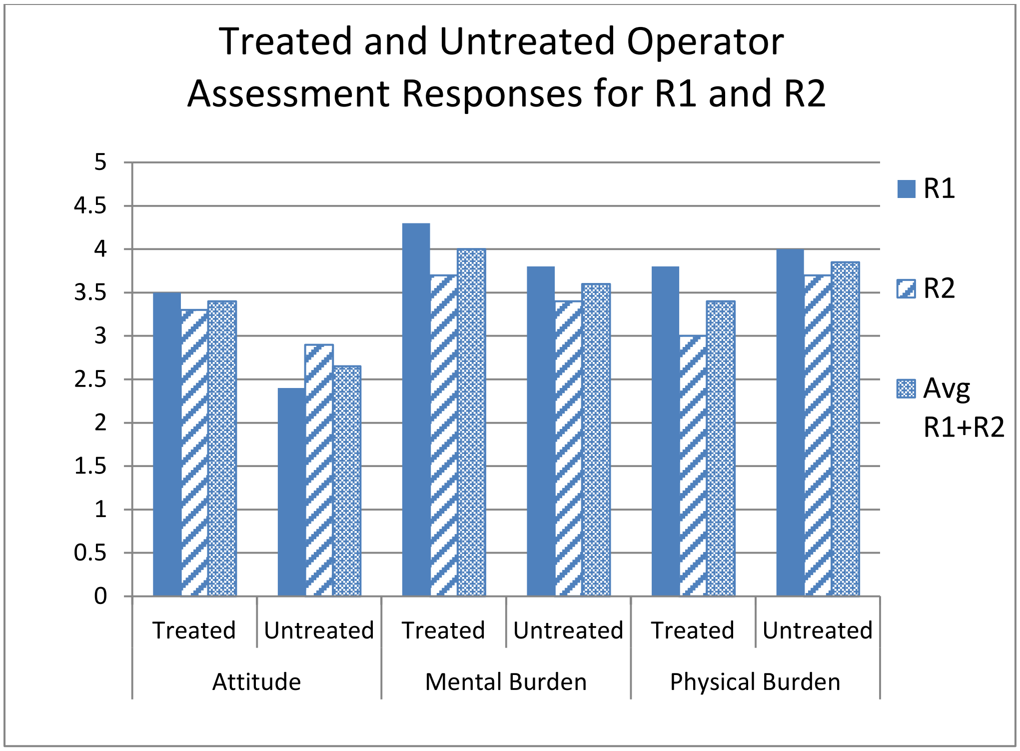


Figure 5.61a. Treated and untreated operator assessment responses for R1 and R2.

Operator responses from the assessments during R3 and R4 are presented in Figure 5.61b. The attitude for both groups appears to have changed very little, although there is a noticeable difference in the mental and physical burden responses.

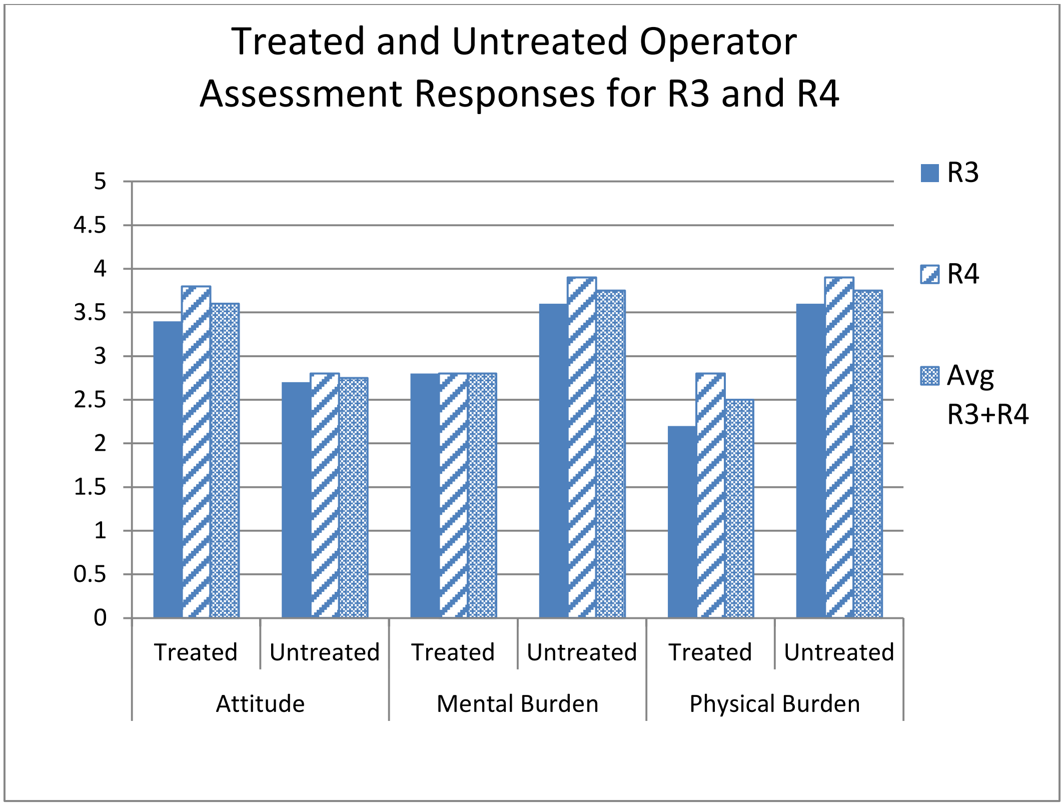


Figure 5.61b. Treated and untreated operator assessment responses for R3 and R4.

The percentage of change for each of these conditions is graphically illustrated in Figure 5.62. Their responses were grouped and averaged using the combined results from R1 and R2 as the baseline for each group and the combined results from R3 and R4 as an indication of the effect of “treatment”. In all cases, a negative value in the graph of Figure 5.61 indicates a reduction or and a positive value an increase of that particular attribute. From the figure, there appears to be little change in attitude between the initial runs and R3/R4 for either treated or untreated teams. However, looking at the burden, the treated teams reported significantly different rankings compared to their untreated counterparts. As can be seen in the data there was a decrease of approximately 40% for both the mental and physical burden of the operators in the treated teams compared to the untreated teams.

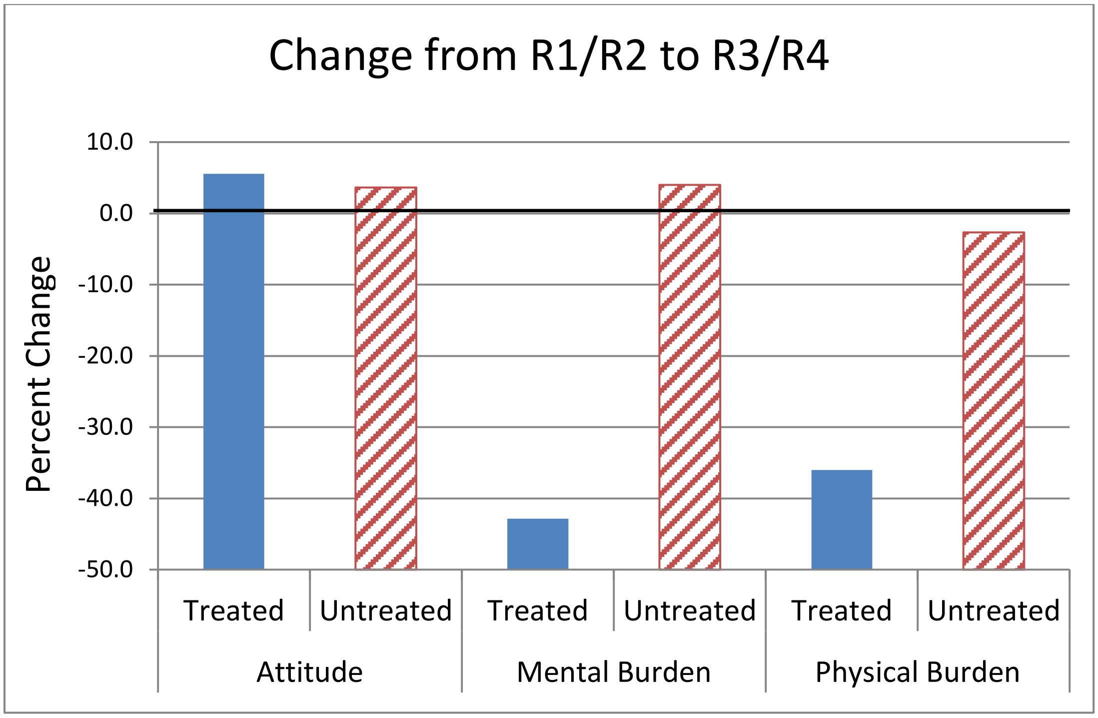


Figure 5.62. Results of self-assessment based on average of both operators and grouped as baseline (R1/R2) and treated or untreated (R3/R4).

In summary, a 3-fold decrease in production defect rate represents a major improvement for most systems, but coupled with the 40% reduction in both mental and physical burden while achieving the defect reduction is a strong indicator of what systematic problem solving in support of Standardization and waste elimination is capable of achieving.

5.6.3. Using LCC Results to Develop a Sustainable Continuous Improvement Probability Model

In this part, the results of the previous learning curve analysis will be used to identify the composite learning ratios (LRs) which will provide the basis for the predictive probability model.

Contextual LCs obtained from this study were combined to form composites or the total average of all the individual contextual LC data used in the previous analysis. The results are shown in Figures 5.63 and 5.64 for the total composite treated and untreated groups respectively. As was done during the contextual LC analysis, each figure consists of three data segments; one from the combined R1/R2 baseline runs, the second from R3 followed by the third segment consisting of R4 data. Each data segment is matched with their corresponding cycles over a 512 total cycle interval. Note, this does not show the complete 1024 cycles because the first 128 cycles were eliminated from the baseline runs and only half of the R3 and R4 runs are showing because the team members rotated positions at the half-way points.

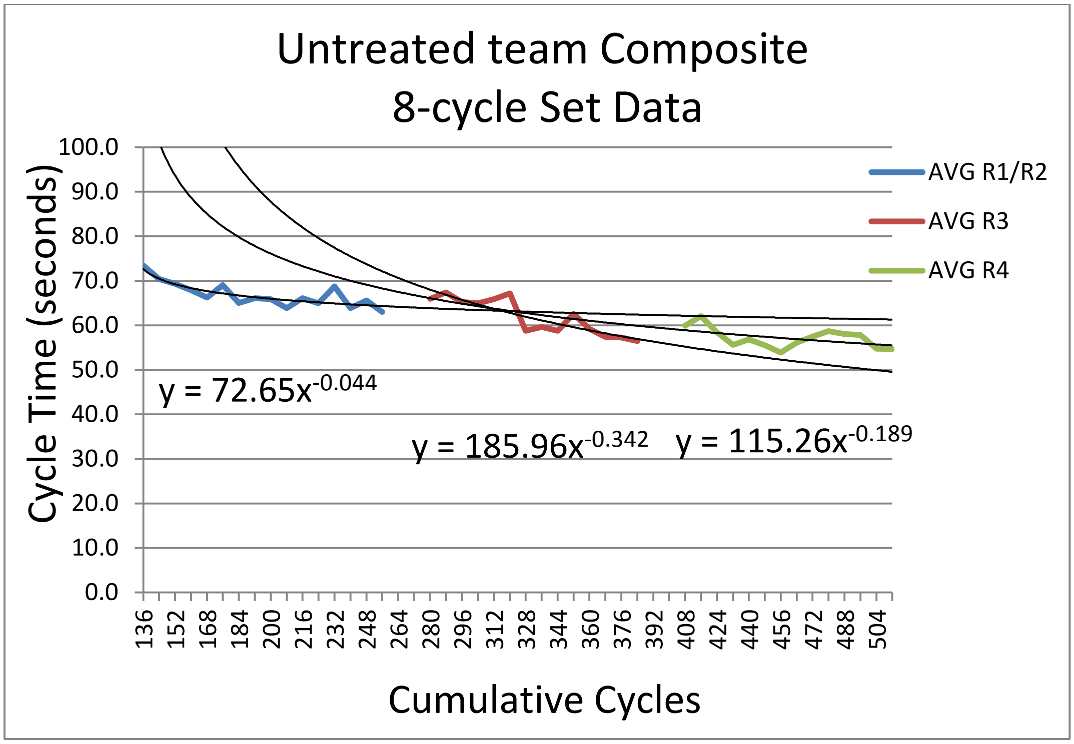


Figure 5.63. Untreated contextual learning curve from composite untreated LCs.

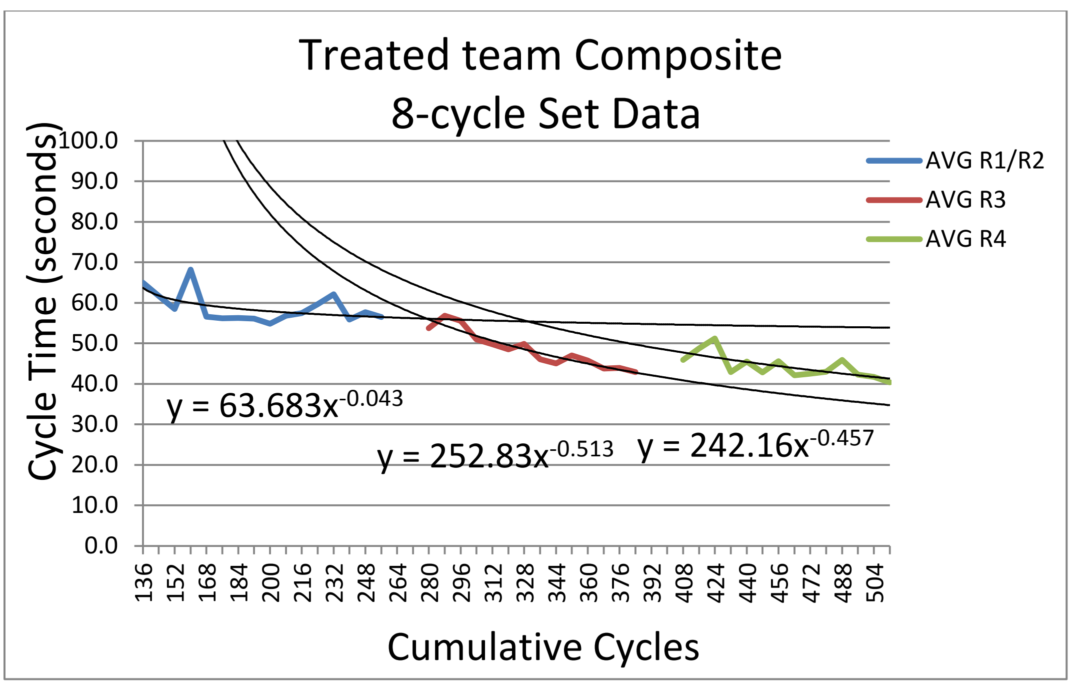


Figure 5.64. Treated contextual learning curves from composite treated LCs.

Each R3 and R4 data segment consists of an average of 8 sets of original 8-cycle data sets used in the previous individual and contextual LC analysis. The figures also include the best-fit trendlines and the power equations associated with them along with the LCCs (exponents) of each data segment. The composite LCCs obtained from both figures are presented in Table 5.48. The composite LCC results are graphed in Figure 5.65 and clearly show the effect of the experimental treatment on the learning rate of the treated and untreated groups.

Table 5.48. Total composite contextual LCCs for treated and untreated teams.

Total Composite Contextual Learning Curve Coefficients (LCC)			
	Treated	Untreated	Learning Ratio (LR)
R1/R2	-0.043	-0.044	1.0
R3	-0.513	-0.342	1.5
R4	-0.457	-0.198	2.3

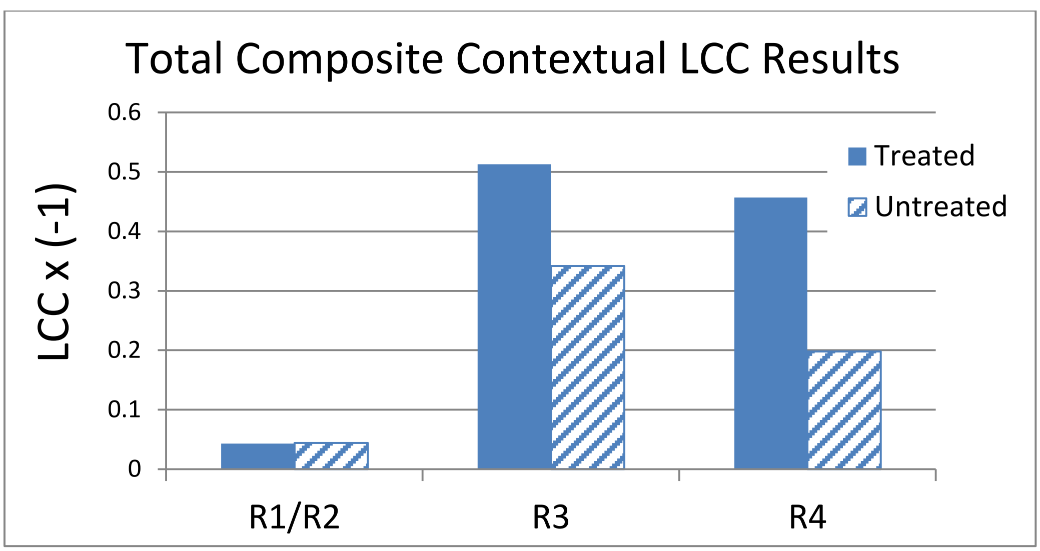


Figure 5.65. Total composite contextual LCC results for treated and untreated teams.

The table also contains the composite learning ratios (LRs) derived from the LCCs in the table. The LRs obtained via this method are graphed in Figure 5.66. From the figure, the LRs associated with each experimental condition are 1, 1.5 and about 2.5 for R1/R2, R3 and R4 respectively.

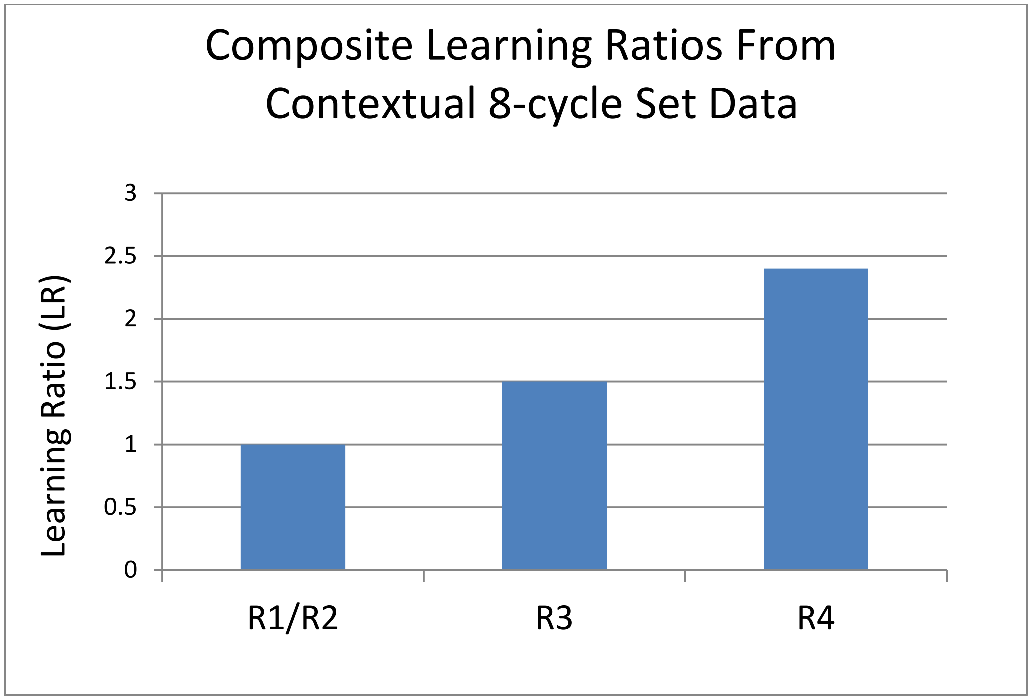


Figure 5.66. Experimentally derived composite learning ratios from contextual LCCs.

Now that it has been experimentally verified that the learning rate and performance of the operators is improved under the experimental conditions of this study, the experimentally determined LRs from Table 5.48 can be assigned to a specific probability model presented in Chapter 4. From this, the hypothetical probability for achieving a sustainable continuous improvement capability can be determined. The assignments are made based upon the basic assumption of this research, namely that improvement activity, represented by the R4 condition, has limited value if it is not preceded by activities designed dot result in Stable and Standard conditions. As the team, and by extension a company or organization, develops from state to state, represented by the experimental conditions for R1/R2, R3 and R4, the probability they will eventually possess the capacity for true continuous improvement increases. Furthermore, because the experimental treatment consists of applying systematic problem solving according the Toyota's 8-step process, establishing the R3 experimental conditions (State 2) of STW+P/S is a prerequisite for R4 (State3). As results, the highest model LR will be assigned to R4, the next highest to R3 and LR = 1.0 to R1/R2. Figures 5.67, 5.68 and 5.69 the predictive probability plots created using the above considerations and based on the experimental result of this study.

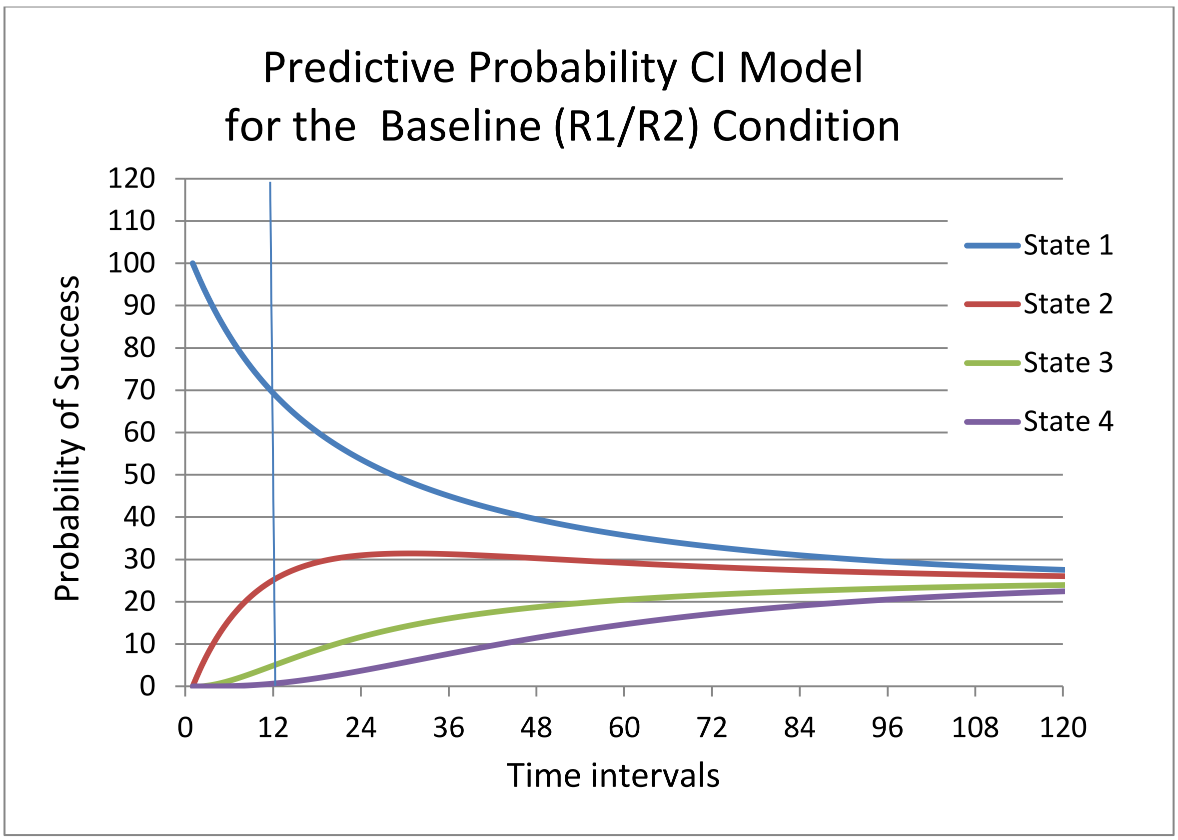


Figure 5.67. Probability plot for LR = 1.0 (R1/R2 condition).

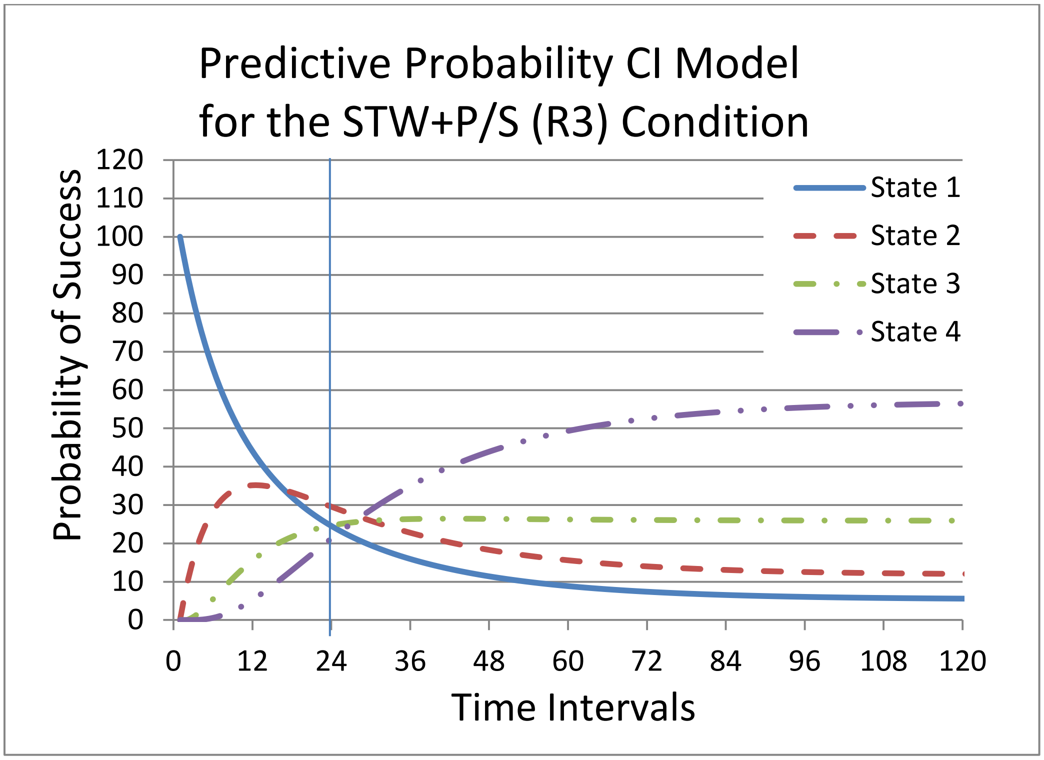


Figure 5.68. Probability plot for LR = 3.0 (R3 condition).

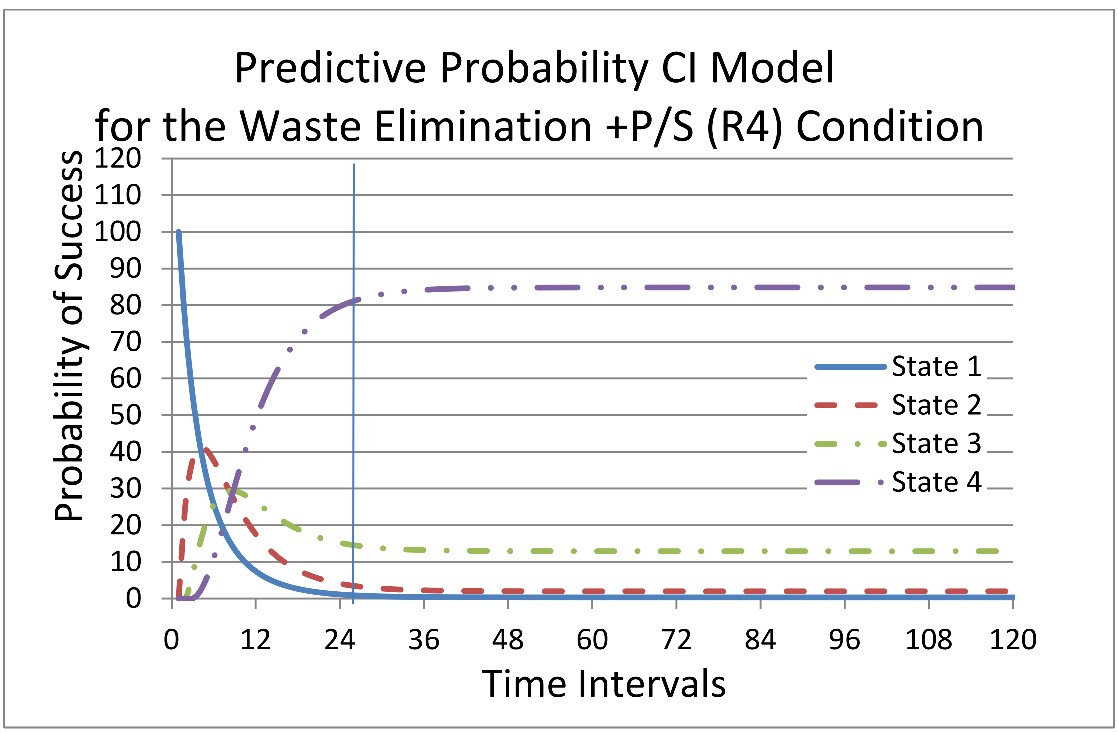


Figure 5.69. Probability plot for LR = 7.5 (R4 condition).

Using the models, it is possible to identify the relative probability of achieving the goal of creating a sustainable continuous improvement capacity within their organizations based on their current state. For example, assuming an organization does not fundamentally change its activities, using the probability plot in Figure 5.67 corresponding to the LR assigned to State 1 (R1/R2), by the end of the next 12 time intervals (approximately months) there is a 70% probability they will remain in State 1, a 25% chance of getting to State 2 and 5% chance of achieving State 3. Under these conditions, there is 0% probability of achieving a sustainable CI capability (State 4). Using the plot in Figure 5.68 determined from the R3 LR, after 24 time intervals those companies have a 25% chance they will be in State1, a 30% chance of being in State 2, about a 25% chance of State 3 and a 20% chance of obtaining State 4. Companies found to be in State 3 already have a 80 % chance of reaching State 4 within 24 time intervals according to Figure 5.69.

To utilize these plots without conducting individual learning curve research in each company, an assessment tool was developed to identify the State a company is currently in. Once the state is identified, the probability plot for that state can be used to determine the likelihood they will create a sustainable CI capability. The statements included in the assessment tool were selected to reflect aspects of the experimental conditions in this study, namely Standard work, systematic problem solving and waste elimination or Kaizen activities. An internal self-assessment was included in the tool to gage each respondents personal assessment of their companies current state.

The assessment tool was trialed on 86 participants in the lean certification program and the results are presented in Figure 5.70. Based on the results approximately

72% of the respondents were found to be in State 1 although only about 58% correctly identify their condition. The other 27% appear to have some Standardization in place and are beginning to use systematic problem solving which puts them into State 2. The assessment tool and their self-assessment (their response to Statement # 25) results were similar. There were no respondents found to be in States 3 or 4 using the tool, although about 12% placed themselves there based on response to Statement # 25. The responses also highlight what appears to be a common problem regarding the use of "Kaizen" and continuous improvement tools., and that is they tend to overestimate their companies true capabilities. Often confusing lean or CI tools with the thinking or methods used to apply the tools. The current assessment tool is presented in Figure 5.71.

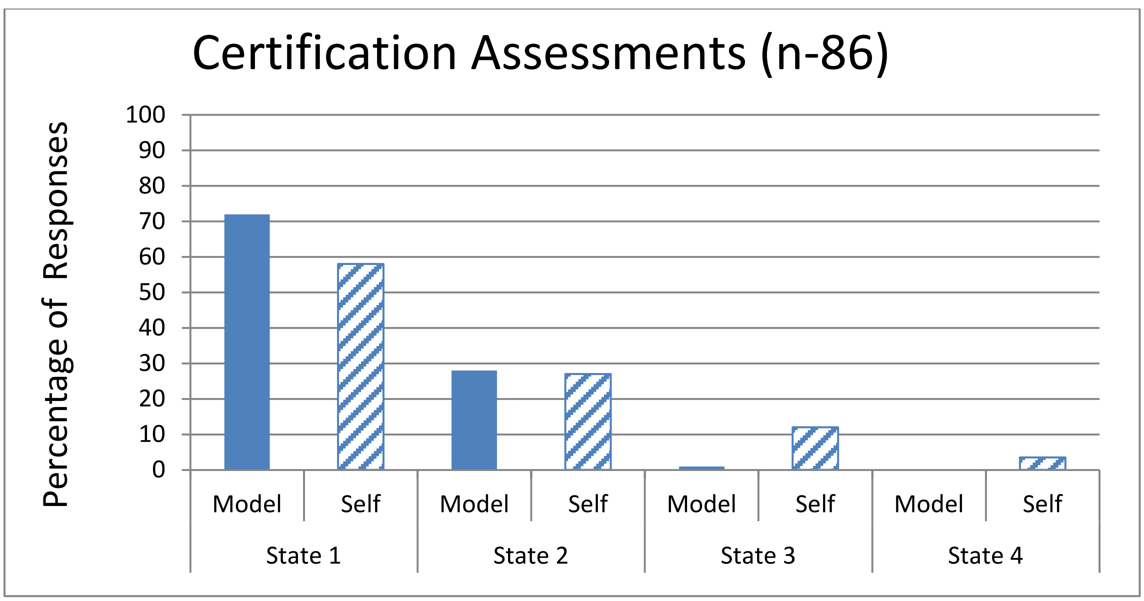


Figure 5.70. Graph showing assessment results from UK Lean Certification participants in terms of the states identified in the model, based on experimental conditions.

Figure 5.71 (next page). Figure showing the assessment questions based on the experimental results.

University of Kentucky True Lean Assessment (rev 120911)

Industry:__________________________ **Number of employees:_______________________**

Number of Divisions:_______________ **Public or Private (circle one)**

NOTE: 1. Individual responses are kept strictly confidential.

2. The name of your organization will not be publicly associated with any responses given.

3. Responses given will be used to validate a proposed transformation model developed as part of a doctoral study conducted at the University of Kentucky

4. Certain responses may be used internally by the UK Lean Systems Program to help us better meet your organization's needs.

Please rank your response to the following questions on a scale of 1 to 10 with 1 being the most negative response possible and 10 being the most positive response possible. Use the same scale to estimate importance.

Please limit your responses to the areas that are familiar to you

	Stationtement/Question	Rank (1-10)	Importance (1 -10)
1	My company has a plan in place to become true lean		
2	Our improvement activities are project based		
3	team members (TMs) know the distinction between normal and abnormal work		
4	We have a role in place to manage the abnormal work of the TMs		
5	TMs perform both normal and abnormal work		
6	We have an effective system in place to help ensure process and performance consistency		
7	We use a systematic problem solving (P/S) method which stresses keeping problems from recurring		
8	Process performance and variation is visible where the work is being performed		
9	We have a role in place (eg the team leader (TL)) to assist the TM in performing Stationndard work (STW).		
10	TMs are encouraged and accountable to perform only normal work (STW)		
11	Human resource (HR) policies are aligned with the goal of being a methods based organization.		
12	We have dedicated areas for P/S and organizational development (Jishuken Room)		
13	Systematic P/S (8-step or equivalent) is taught and used by everyone		
14	TMs expected to conduct P/S activities are adequately trained in systematic P/S before using it		
15	Our organization has qualified P/S trainers		
16	STW is always updated as the result of P/S activities		
17	TMs underStationnd the goals and targets of the organization in a way they can relate to		
18	PDCA thinking is common in my company		
19	Problems are immediately identified and addressed at all levels of the organization		
20	If the root cause of a problem is found to be in another part of the company, it will be effectively addressed		
21	Kaizen is part of our daily routine		
22	Stationndardization is part of your daily routine		
23	We always begin Kaizen activities by ensuring we are meeting Stationndard conditions		
24	All levels and departments in my organization are aligned to the same purpose and methods to achieve a culture of continuous improvement (true lean)		
25	At the CURRENT time, estimate the probability your company will develop a true lean culture (suStationined continuous improvement environment). scale 1 to 10		

CHAPTRER 6: SUMMARY OF LEARNING CURVE STUDEIS AND CONTINUOUS IMPROVMENET MODEL DEVELOPMENT

The original null hypotheses of this study are restated below. They are:

1. H_1: Initiating the use of *Standard work along with 8-step problem solving thinking* to eliminate obstacles to performing normal work does not significantly effect *individual team member learning* as opposed to allowing team members to perform both normal and abnormal work.

2. H_2: *Introducing formal concept of the seven-wastes and facilitating 8-step problem solving to eliminate them does not significantly effect individual team member learning* as opposed to relying on individual notions of waste and improvement opportunities.

3. H_3: System productivity is not affected by the application of systematic problem solving to support Standardization and waste elimination activities used in this study.

Hypotheses 1 and 2 were addressed through the results from both treated and untreated teams to the conditions in R3 and R4 respectively. Unfortunately, due to the labor intensive nature and time constraints of the students involved in the experiments permitted only four teams to participate in the study. As a result, there are essentially only 4 data points in each of the statistical analysis. While in some instances, the t-test results support rejecting null hypotheses 1 and 2 stated above, for the most part the validity of the results depend on the observation of trends.

The results of the contextual LCC analysis are presented in Table 6.1. This table contains the LCC and p-values from paired t-test analysis of treated and untreated operators in all runs and combinations represented by cases 1 to 4. The R1/R2 and R3/R4 conditions represent the combined averages from their constituent runs. Statistical significant paired t-test results at the 90% level are highlighted in bold print. The paired t-test compares the means of the data set as each member of the population moves from one condition to the next.

Table 6.1 (originally 5.26). Average contextual LCC results and paired t-test p-values from R1/R2 to R3 experimental runs.

Case		R1/R2		R3		R1/R2 to R3	
		Avg LCC		Avg LCC		p-Value	
		Treated	Untreated	Treated	Untreated	Treated	Untreated
1	Operator A	-0.039	-0.027	-0.532	0.273	**0.01**	**0.004**
	Operator B	-0.048	-0.055	-0.477	0.433	**0.051**	**0.019**
		R3		R4		R3 to R4	
2	Operator A	-0.532	-0.273	-0.499	0.062	0.908	0.213
	Operator B	-0.477	-0.433	-0.413	0.320	0.80	0.509
		R1/R2		R4		R1/R2 to R4	
3	Operator A	-0.039	-0.027	-0.499	0.062	**0.084**	0.928
	Operator B	-0.048	-0.055	-0.413	0.320	**0.054**	0.106
		R1/R2		R3/R4		R1/R2 to R3/R4	
4	Operator A	-0.039	-0.027	-0.516	-0.168	**0.002**	0.417
	Operator B	-0.048	-0.055	-0.445	-0.377	**0.004**	**0.017**

A statistically significant result indicates the response of the teams in the group were different for the stated conditions tested (e.g., R1/R2 to R3, etc.). The results were discussed in three cases.

Case 1: Baseline (R1/R2) to R3: The t-test results for R3 in Table 6.1 indicate there is a statistical ly significant difference in the responses of both operators for each group of treated and untreated teams between their baseline (R1/R2) responses and the R3 (Standard work (STW) + P/S) conditions. Figure 6.1 illustrates the results for R1/R2 and R3 listed in Table 6.1 and shows visually the LCC results for R1/R2 and R3 data are significantly different than their R1/R2 conditions. It also appears the R3 data may be different from each other.

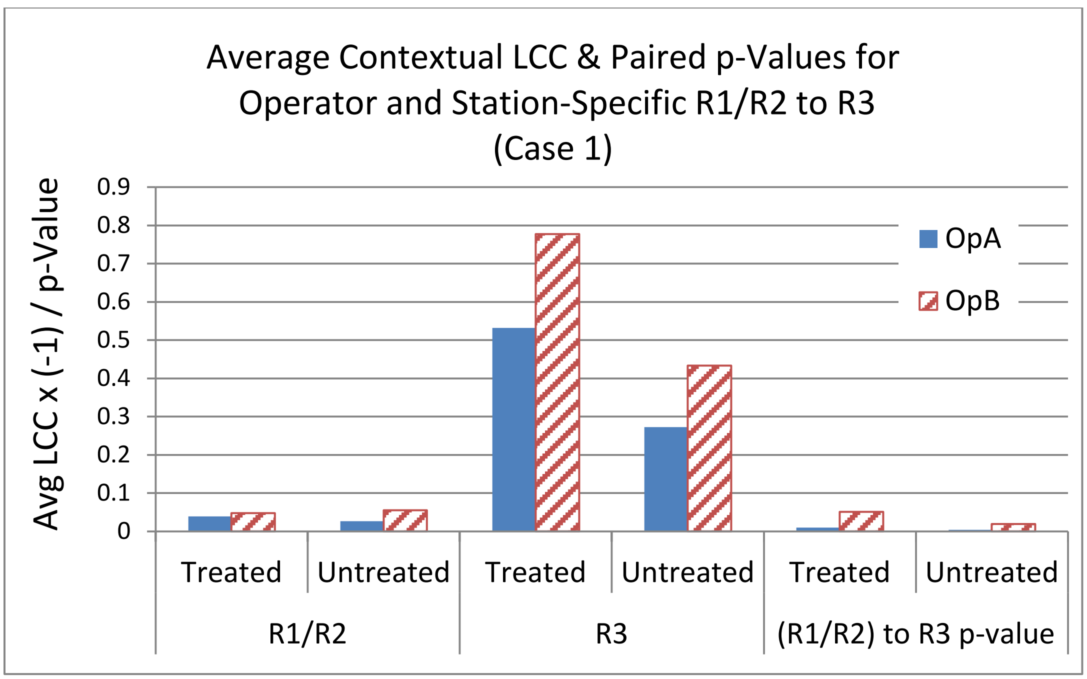


Figure 6.1 (originally 5.23). Graphical representation of average contextual LCC results and p-value results for R1/R2 and R3 presented in Table 6.1.

Two-sample t-test analysis to determine if there is a significant difference between the treated and untreated responses for R3 and R4 are summarized in Table 6.2.

The summary shows only the treated and untreated R3 Operator A LCC results for R3 are significantly different (at the >95% confidence level) to each other, while both Operator B's LCC responses were statistically similar to each other. One possible explanation of these results is that while both groups are engaged making improvements, the nature of the processes used is effecting the consistency of the learning and engagement of the operators differently.

Table 6.2 (originally 5.23). Summary of two-sample t-test analysis of contextual Operator-specific LCC data for R3 and R4 treated and untreated teams.

R3 Contextual LCC Data			R4 Contextual LCC Data		
Treated vs Untreated teams			Treated vs Untreated teams		
	Operator A	Operator B		Operator A	Operator B
Observations	4	4		4	4
T-Stat	-2.501	-0.336	T-Stat	-1.058	-0.478
T-Critical (2-tail)	2.45	2.45	T-Critical (2-tail)	2.45	2.45
P-value (2-tailed)	**0.046**	0.748	P-value (2-tailed)	0.331	0.649

Case 2: R3 to R4: The paired t-test analysis of LCC responses shown in Table 6.1 for treated and untreated operators going from R3 to R4 showed no statistically significant difference in response for either the treated and untreated groups. The two-sample t-tests for R4 show there is a significant difference in the LCC results of the treated and untreated Operator A. The graph showing the case 2 results is presented in Figure 6.2 and shows graphically the high variation between the untreated LCC results compared to the treated results. Also from Figure 6.2, it can be seen that the untreated

LCC results are again smaller than their treated counterparts. The difference in consistency of the LCC results is important because it shows the learning rate for both treated operators were similar while the untreated operators experienced very different leaning rates. Also, as seen in Figure 6.2, the LCC of the untreated operators decreased going from R3 to R3, resulting in an increasingly large gap between the learning rate of the treated group and the untreated group. .

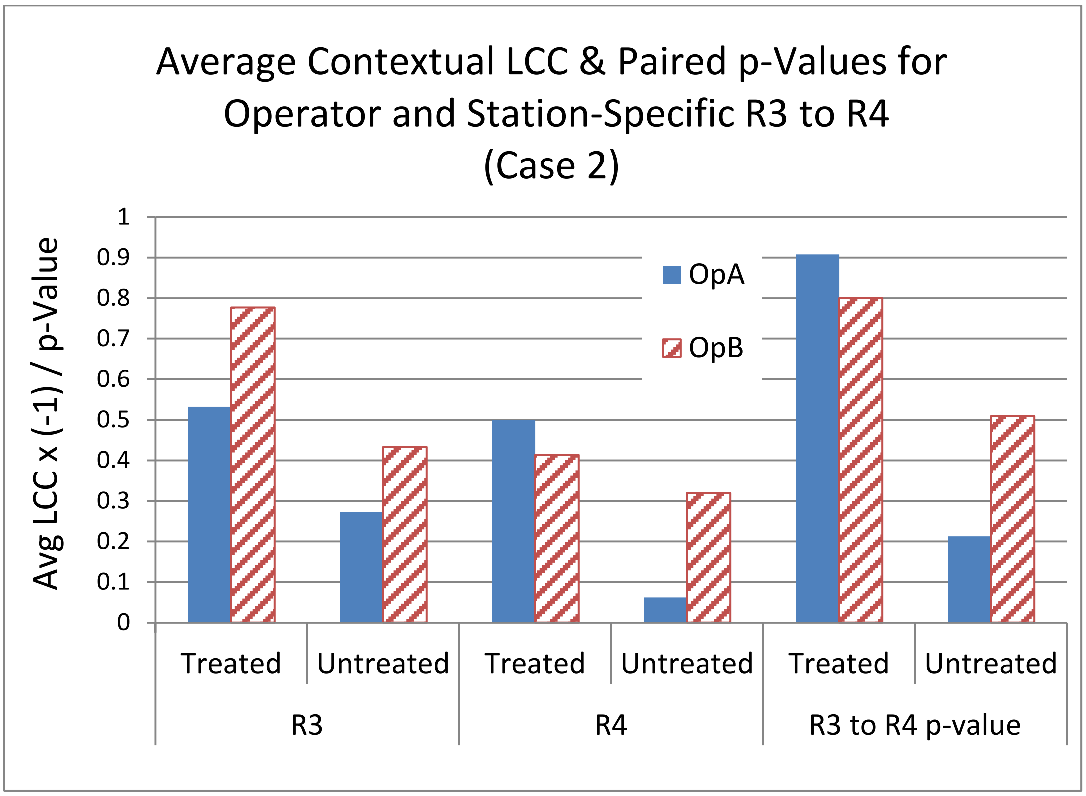


Figure 6.2 (originally 5.24). Graphical representation of average contextual LCC results and p-value results for R3 and R4 presented in Table 6.1.

Case 3: Baseline (R1/R2) to R4: The paired t-test results for the LCC responses going from baseline (R1/R2) conditions to R4 are also shown in Table 6.1. According to the analysis there is a significant difference (90% confidence level) in LCC response for both treated operators going fromR1/R2 to R4. Even though the paired t-test for untreated Operator B was slightly above the 0.10 limits for the 90% level, the results again show a high amount of variation between untreated Operator A and Operator B's responses compared to both treated operators seen visually in Figure 6.3.

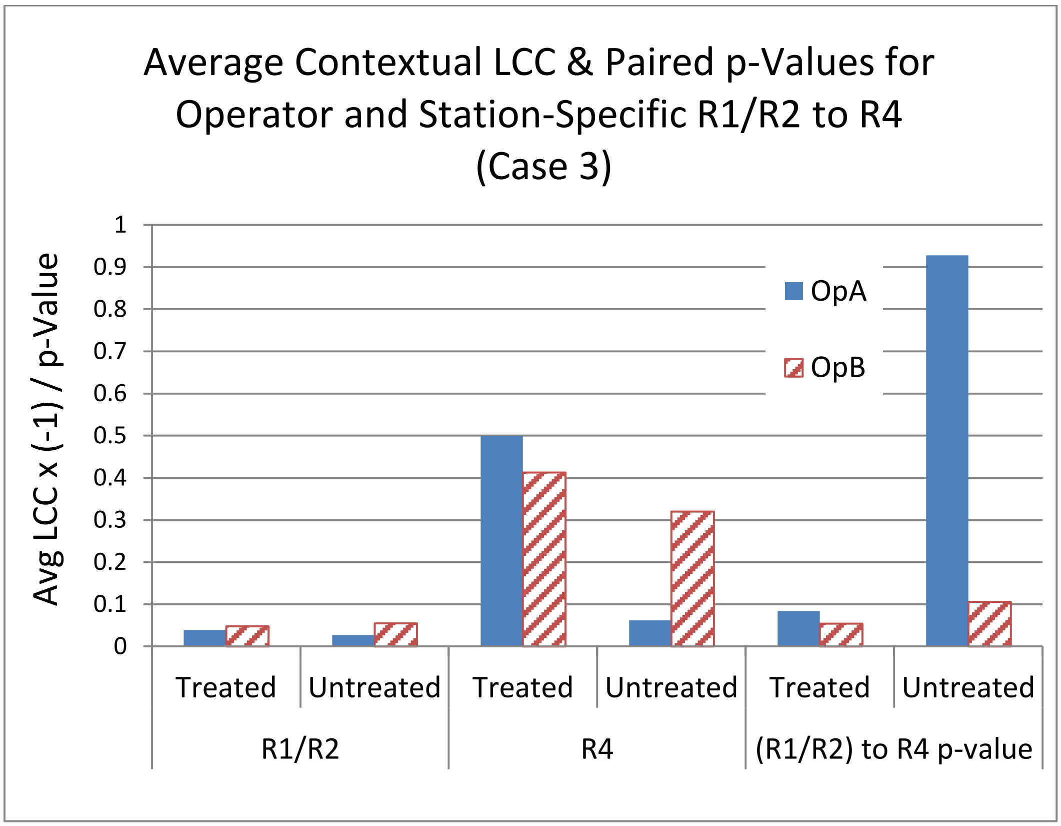


Figure 6.3 (originally 5.25). Graphical representation of average contextual LCC results and p-value results for R1/R2 and R4 presented in Table 6.1.

Finally, Figure 6.4 illustrates the LCC and p-value data for R1/R2 to R3/R4 shown in Table 6.1. As expected the figure is very similar to Figure 6.3 an shows that while there is a significant difference between the LCC results of both treated operators and their baseline, only untreated Operator A is statistically different than its' baseline LCC results at the 90% level.

In summary, treated operators (team members) did exhibit statistical different learning (LCC) responses than their untreated counterparts in Cases 1, 3 and 4. In case 3, one untreated operator also had a similar response. While the statistical results were mixed, perhaps in part due to small sample sizes, in all cases, the learning rates obtained from the treated operators were greater than those of their untreated counterparts. In addition, the untreated operators also exhibited a much larger variation in learning rate for all cases compared to their treated counterparts.

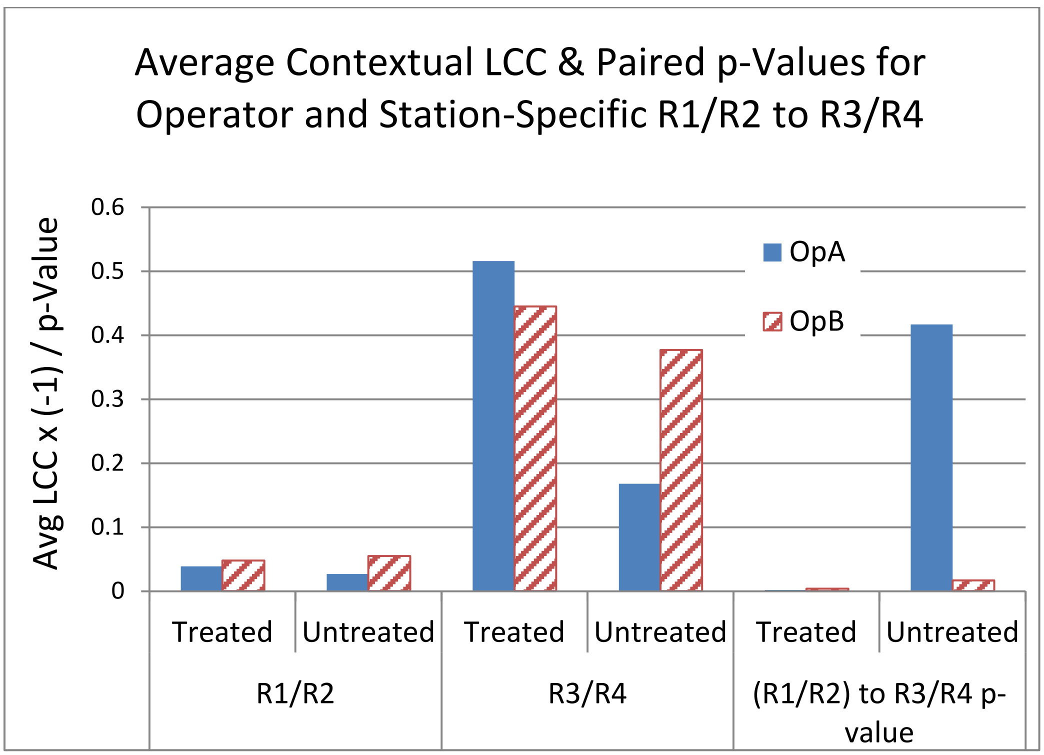


Figure 6.4 Graphical representation of average contextual LCC results and p-value results for R1/R2 and R3/R4 presented in Table 6.1.

Hypothesis 3 was addressed using total throughput time (TPT) results based on total cycle time (TCT) data from both operators, including the wait time (WT) between them as determined by the total WT measured per 16-cyle segment. System learning and performance are determined using the total throughput time (TPT) results for both LCC and cycle time (CT). The TPT results provide a realistic assessment of learning and performance in the system because the occurrence of WT between Stations is very common in production environments and it is also an indication of work imbalance.

The total average TPT LCC results are presented in Table 6.3 and illustrated in Figure 6.5. The baseline LCC values are much higher than for the individual and contextual LCC values because the TPT analysis uses the complete 256 cycles of the LC. The TPT LCC results are similar to the individual contextual results. Figure 6.5 shows the LCC of the treated teams are consistently higher than their untreated counterparts. The results shown in Figure 6.5 and Table 6.3 were used to calculate the decrease in LCC going from different experimental runs to another shown in Figure 6.6. The figure shows that while there is little difference in learning of the two groups going form R1/R2 to R3, it changes considerably going from R3 to R4, with the untreated teams experiencing about almost 3 times more loss in LCC than their treated counterparts.

Table 6.3. Total average TPT LCC result for R1/R2, R3, R4 and R3/R4.

	Total Average TPT LCC Results for (OpA+OpB & Operator B+OpA)			
	R1/R2	R3	R4	R3/R4
Treated	0.165	0.116	0.087	0.102
Untreated	0.139	0.086	0.027	0.057

The summaries of paired t-test analysis of the TPT LCC results shown in Figure 6.5 are presented in Table 6.4. According to the paired t-test analysis, there is a statistical significant difference in the treated teams' LCC response going from R1/R2 to

R3 and overall from R1/R2 to the combined R3/R4 condition compared to the untreated group's LCC results.

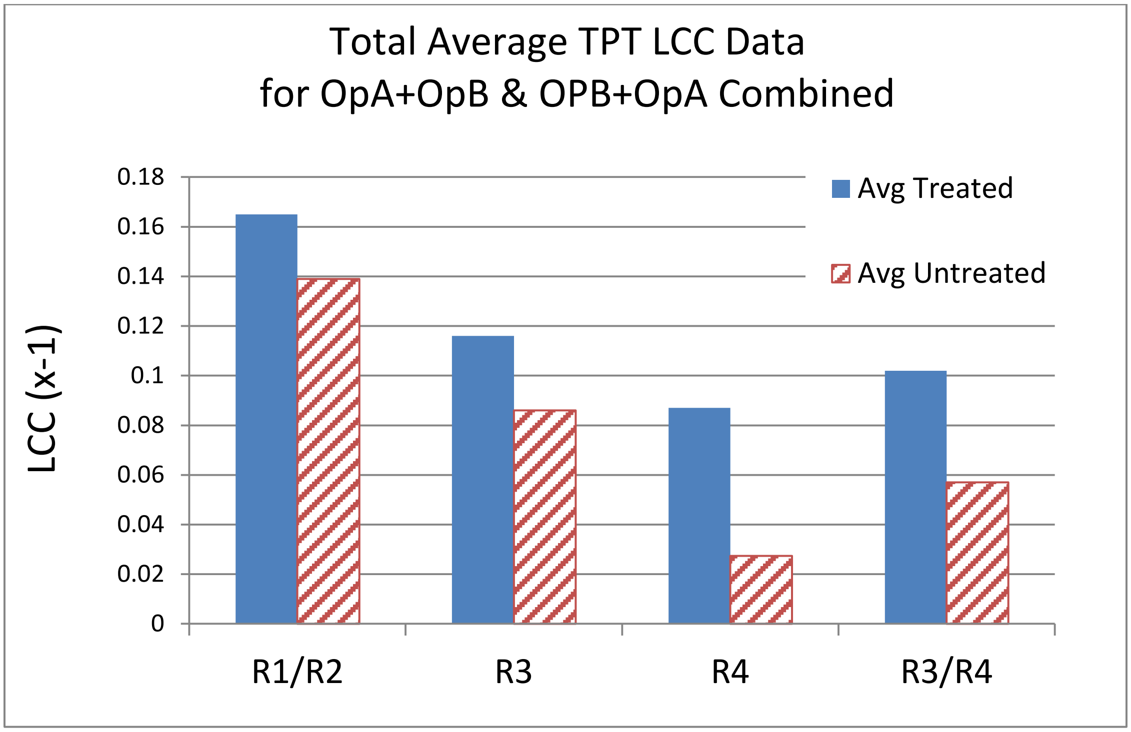


Figure 6.5. Total average TPT CT results for R1/R2, R3, R4 and R3/R4.

Table 6.4 (originally 5.45). Summary of Paired t-test results for treated and untreated TPT LCC data.

Treated TPT LCC Data (OpA+OpB & OpB+OpA)				
	R1/R2 to R3	R3 to R4	R1/R2 to R4	R1/R2 to R3/R4
Observations	4	4	4	4
T-Stat	-2.585	-0.650	-2.095	-3.255
T-Critical (2-tail)	3.182	3.182	3.182	3.182
P-value (2-tailed)	**0.081**	0.562	0.127	**0.047**
Untreated TPT LCC Data (OpA+OpB & OpB+OpA)				
	R1+R2 to R3	R3 to R4	R1+R2 to R4	R1/R2 to R3/R4
Observations	4	4	4	4
T-Stat	-1.310	-1.924	-2.191	-1.943
T-Critical (2-tail)	3.182	3.182	3.182	3.182
P-value (2-tailed)	0.282	0.150	0.116	0.147

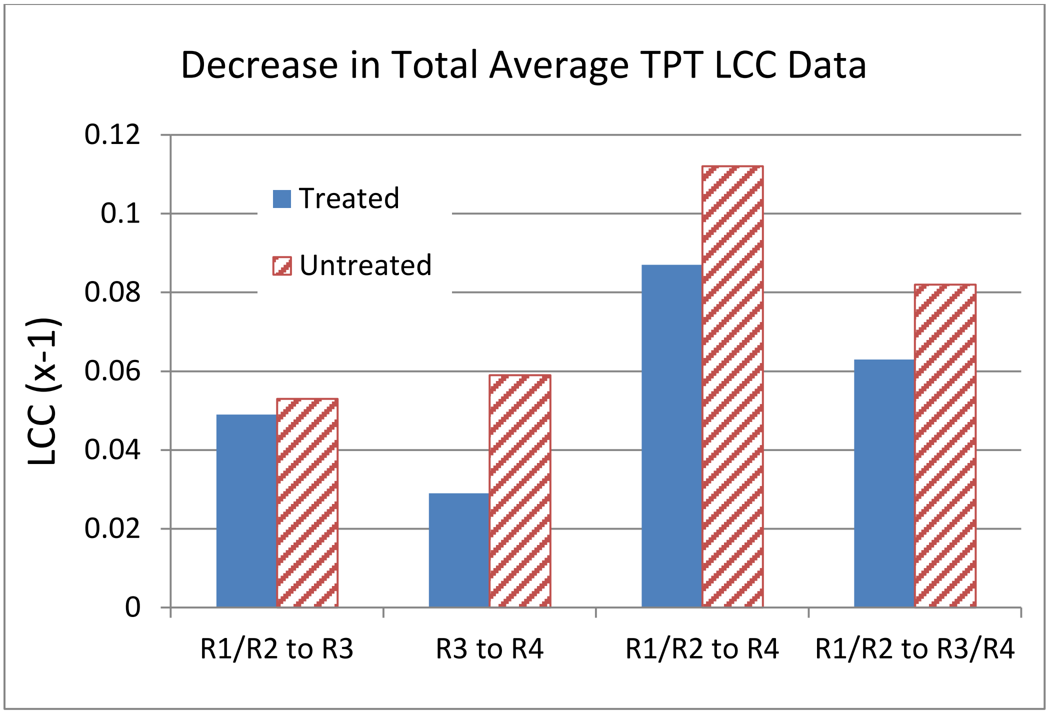


Figure 6.6 (originally 5.56). The change in total average TPT LCC data for OpA+OpB and OpB+OpA combined going from R1/R2 to R3, R3 to R4 and R1/R2 to R3/R4.

The TPT cycle time (CT) results are presented in Table 6.5 and illustrated in Figures 6.7 and 6.8. Paired t-test and two-sample t-test statistical analysis was performed on the combined results from R1/R2 and R3/R4 and the results are summarized in Table 6.6. The results show that the overall response of both the treated and untreated CT results going from R1/R2 to R3/R4 was significantly different then the baseline results of each group. However, the two-sample t-test results indicate that even though both groups were significantly different from their starting condition results, the treated teams TPT CT results were significantly different than their untreated counterparts at > 95% confidence level.

The TPT results from both the CT and LCC show the use of systematic problem solving to support Standard work and waste elimination produced significantly different learning rate (LCC) and CT results compared to teams applying less formal and non-systematic problem solving to address problems. Although statistical analysis of the effect of treatment on individual run conditions (R3 and R4) were inconclusive, two-sample t-tests on the combined results of R1/R2 and R3/R4 were significant.

Table 6.5. The average TPT CT results for R1/R2, R3 and R4.

Avg TPT per Cycle			
	R1/R2	R3	R4
Avg Treated	154	114	94
Avg Untreated	176	143	132

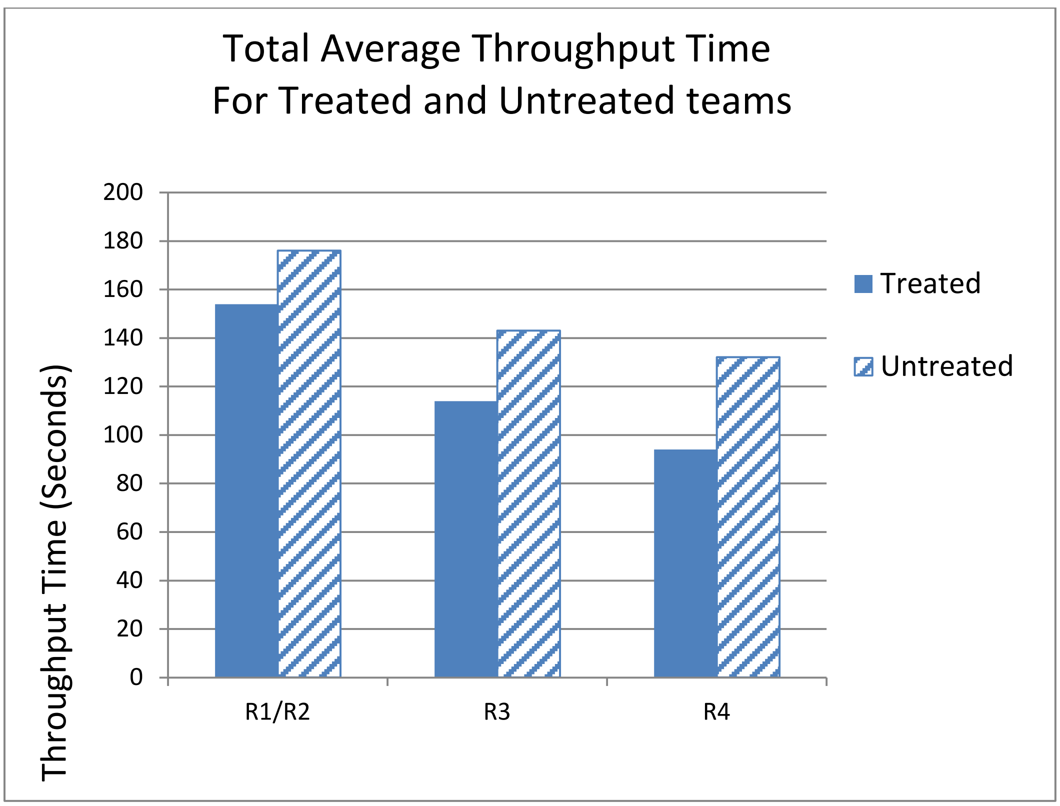


Figure 6.7. Total average TPT CT for treated and untreated R1/R2, R3 and R4.

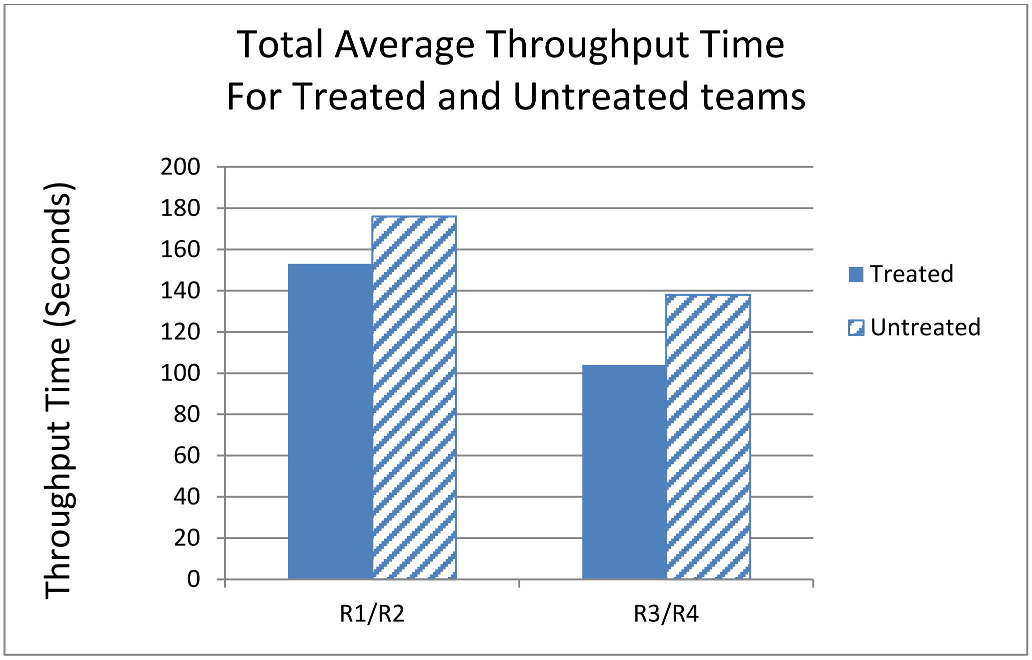


Figure 6.8. Total average TPT CT for treated and untreated R1/R2 and R3/R4.

Table 6.6. Summary of Paired and Two-Sample t-test results for treated and untreated R1/R2 and R3/R4 TPT CT data.

Treated TPT CT Data (OpA+OpB & OpB+OpA)				
	Paired t-Test		Two-Sample t-Test	
	R1/R2 to R3/R4		Treated vs Untreated	
	Treated	Untreated	R1/R2	R3/R4
Observations	4	4	4	4
T-Stat	2.683	2.801	-1.093	-4.012
T-Critical (2-tail)	3.182	3.182	2.45	2.45
P-value (2-tailed)	**0.075**	**0.068**	0.316	**0.007**

6.1. Additional Learning from this study

The occurrence of “induced autonomous “ learning is a term introduced by the author in chapter two to describe the learning condition where experienced operators (or team members) use the concepts examined in the study, namely Standardization and waste elimination using systematic problem solving, as the foundation for true continuous improvement. The hypothetical assumption of induced autonomous learning is illustrated in Figure 6.9 reproduced below. Figures 6.10 and 6.11 show the composite contextual LCs obtained from the treated and untreated experimental data. The LCs in both graphs exhibit some change in the LC slope which is a feature of induced autonomous learning. However the difference in the magnitude of the learning rates associated with each group is significant.

The ratio of the LCCs determined from the power equations associated with each LC were used to create the learning ratios (LRs) graphed in Figure 6.12. The LRs indicate the rate of learning associated with using systematic problem solving to eliminate abnormalities interfering with the performance of normal (standard) work (i.e., R3) is about 50% greater than the learning rate exhibited by teams identifying and addressing problems and abnormalities using less systematic, more individually oriented problem solving methods (untreated R3 and R4).

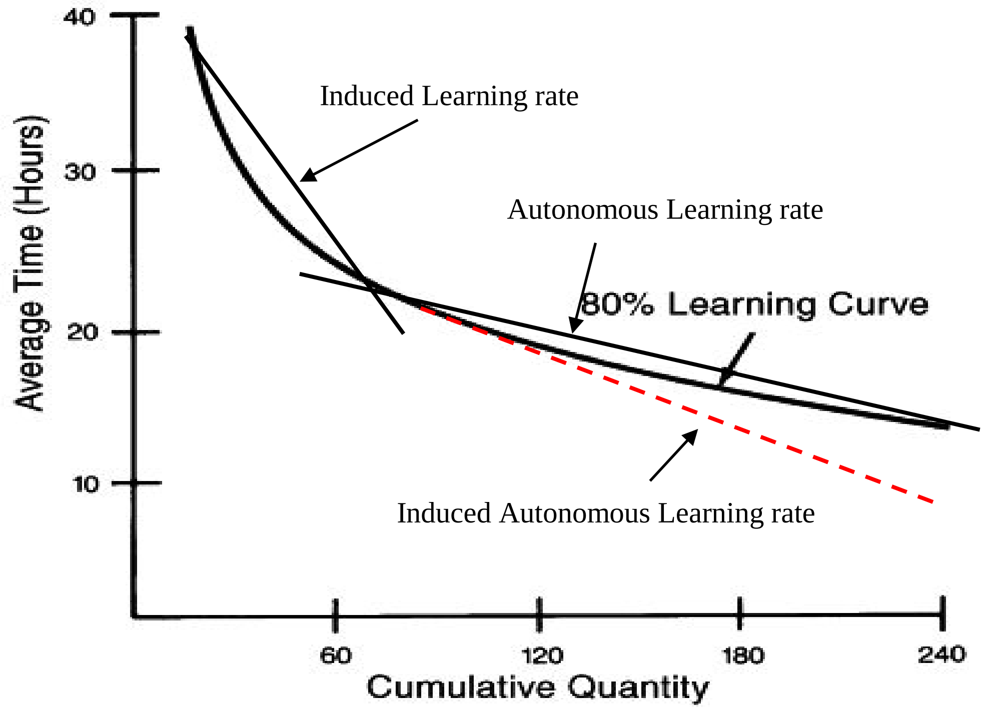


Figure 6.9 (originally 2.1). Illustration of a learning curve showing Induced and Autonomous learning regions along with the hypothesized Induced Autonomous learning region as the result of systematic P/S at team member /work interface.

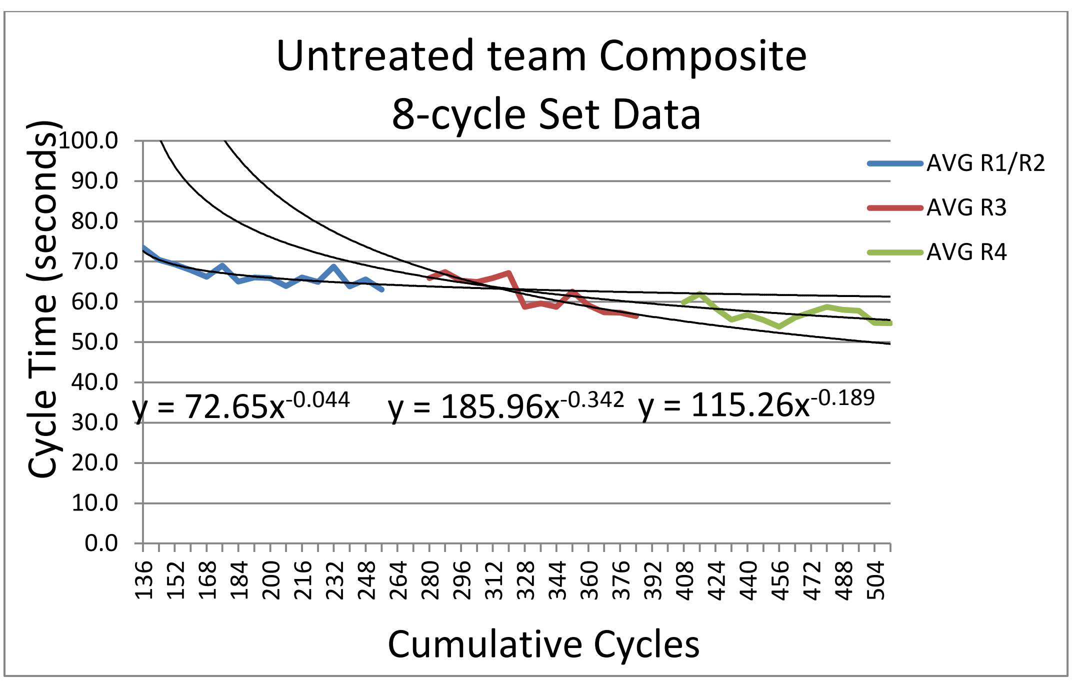


Figure 6.10 (5.61). Untreated contextual learning curve from composite untreated LCs.

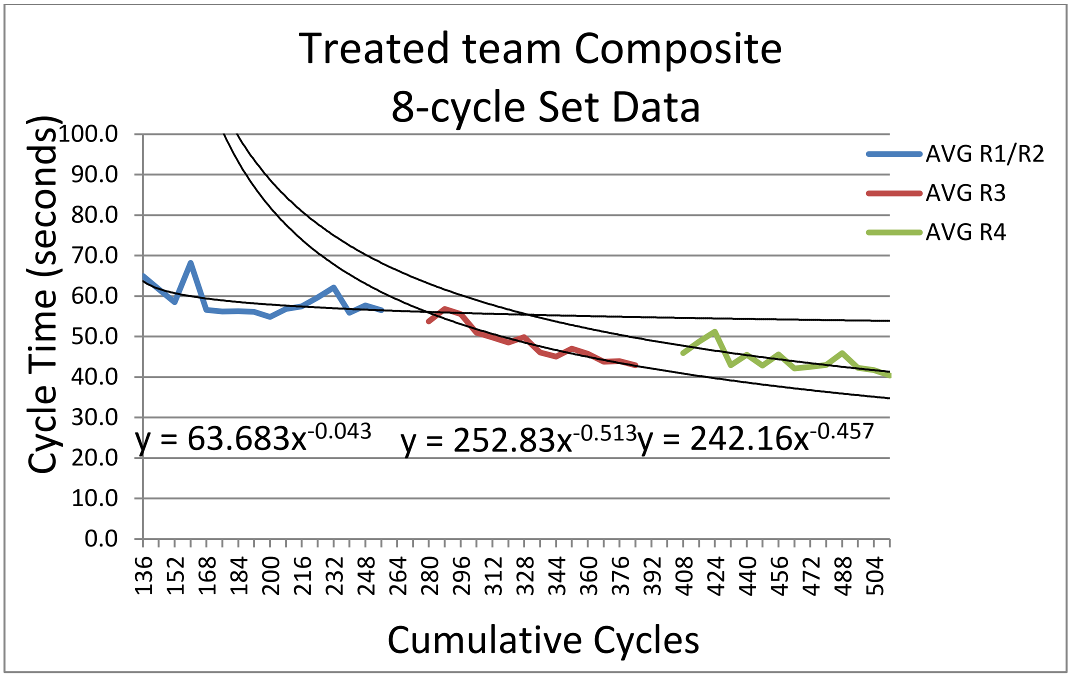


Figure 6.11 (5.62). Treated contextual learning curves from composite treated LCs.

The LR for R4 indicates training to identify specific forms of waste coupled with applying the same systematic problem solving method to eliminate it and maintain normal (Standard) work conditions results in an additional 62.5% increase in team member learning rate compared to team members in the untreated (untrained) teams. The association of these LRs with the experimental conditions prevalent during R1/R2, R3 and R4 are the basis for the development of predictive probability model and its assessment tool as a means to provide guidance for organizations wanting to develop true continuous improvement capacity.

In addition to identifying an induced autonomous learning state and creating LRs associated with each experimental run conditions (states), several major behavioral trends were observed from the data. The first trend seen consistently in the results is that the treated teams which conducted systematic problem solving to eliminate abnormal work (following Standard work) in R3showed higher LCC values on average than their untreated counterparts who were encouraged to identify and solve problems informally, and did not follow the same Standard work procedures.

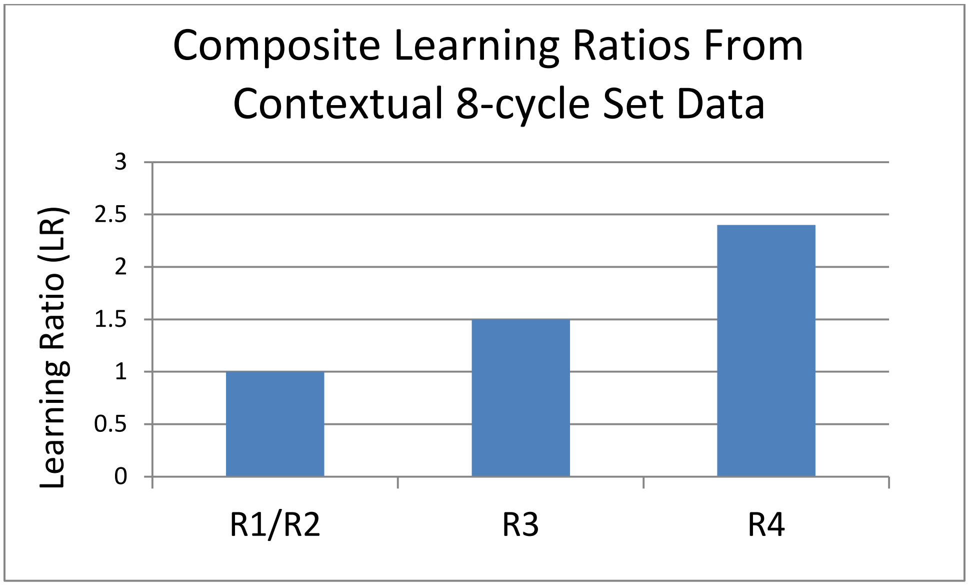


Figure 6.12 (originally 5.63). Experimentally derived composite learning ratios from contextual LCCs.

See Figure 6.13 for individual and contextual LCC results and 5.74 for TPT LCC results. This trend continued into R4 where the treated teams were taught formal forms of waste and used systematic problem solving to eliminate them as they occurred in their processes. Again the average LCC results from the teams were higher than their untreated counterparts who continued with the same informal improvement methods they employed during R3.

The second major trend observed in all the average LCC results was the difference in the rate of decrease in learning rate experienced by the two groups. As each group progressed from the baseline runs (R1/R2) to R3 and R4, the rate of LCC decrease was observed to be more rapid for untreated teams then their treated counterparts. This effect is illustrated in Figures 6.14 for the contextual LCC results and Figure 6.15 for TPT LCC results. Both results appear to validate the hypothesis graphically illustrated in Figure 6.16.

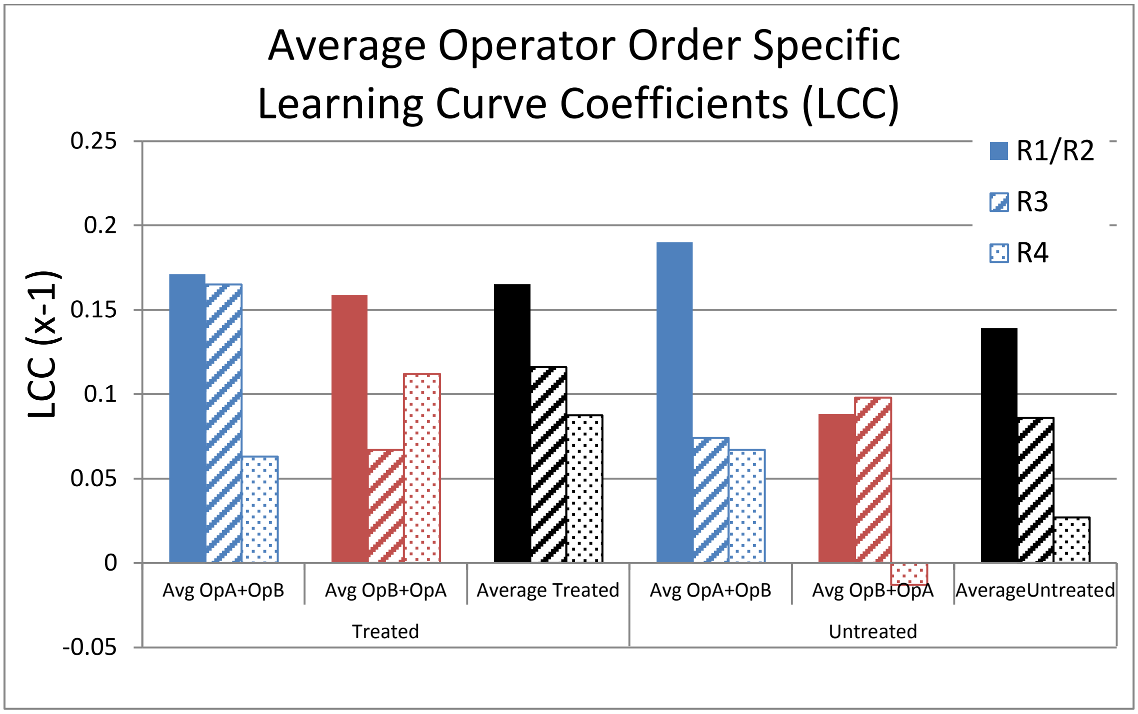


Figure 6.13 (originally 5.53). Average operator order specific LCC results for R1/R2, R3 and R4.

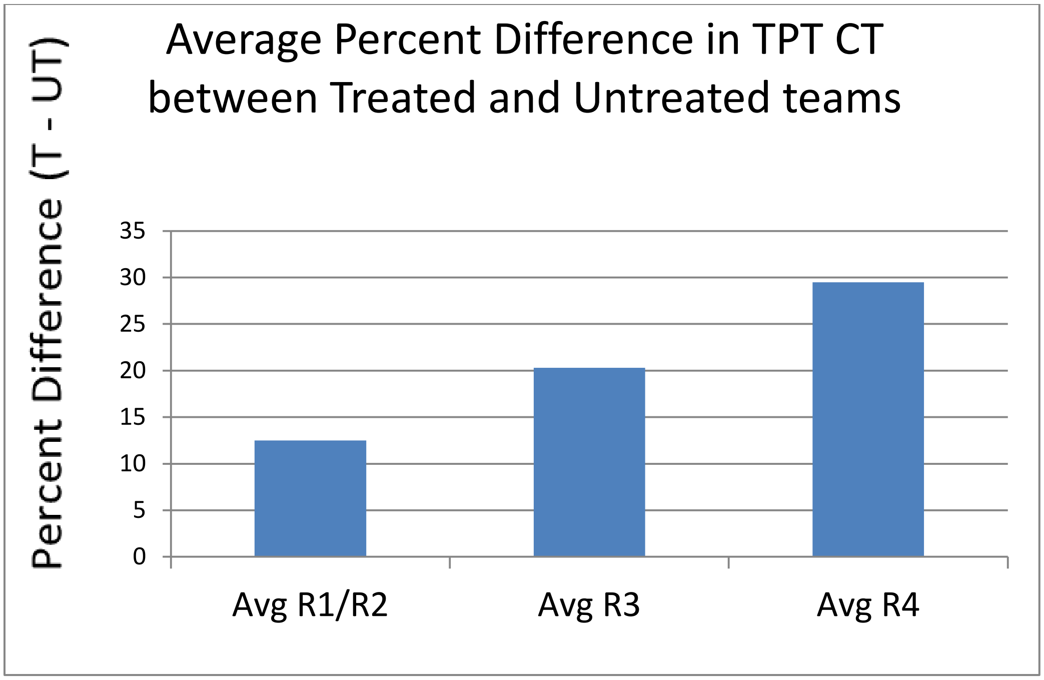


Figure 6.14 (originally 5.38). Percent difference in TPT CT between treated and untreated teams for R1/R2, R3 and R4.

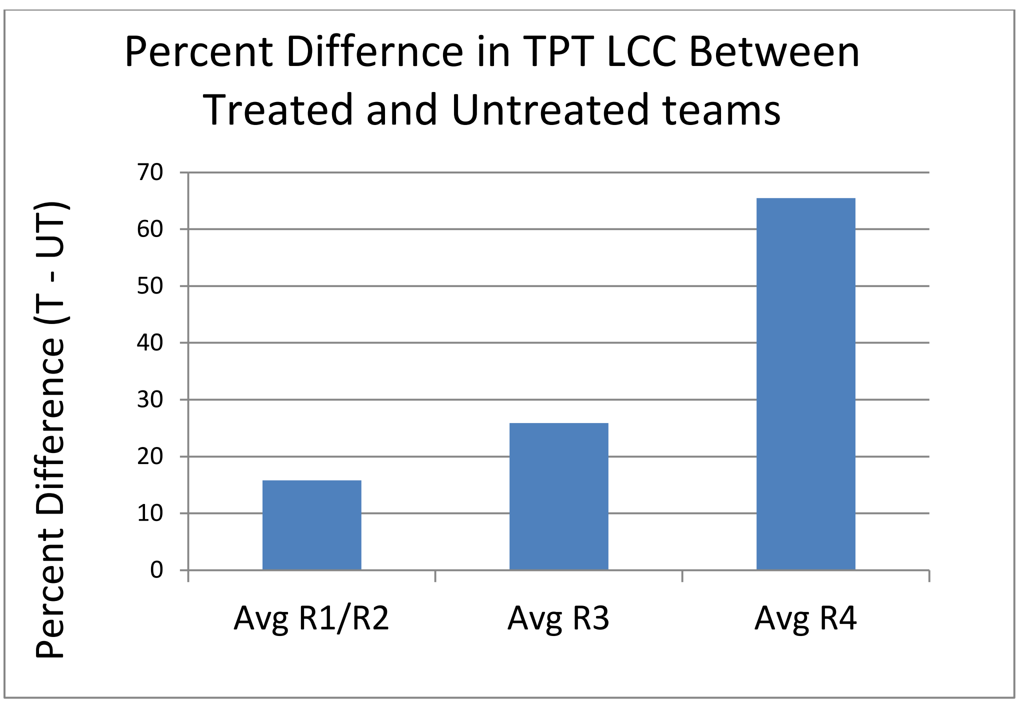


Figure 6.15 (originally 5.54). The percent difference in TPT LCC between treated and untreated teams.

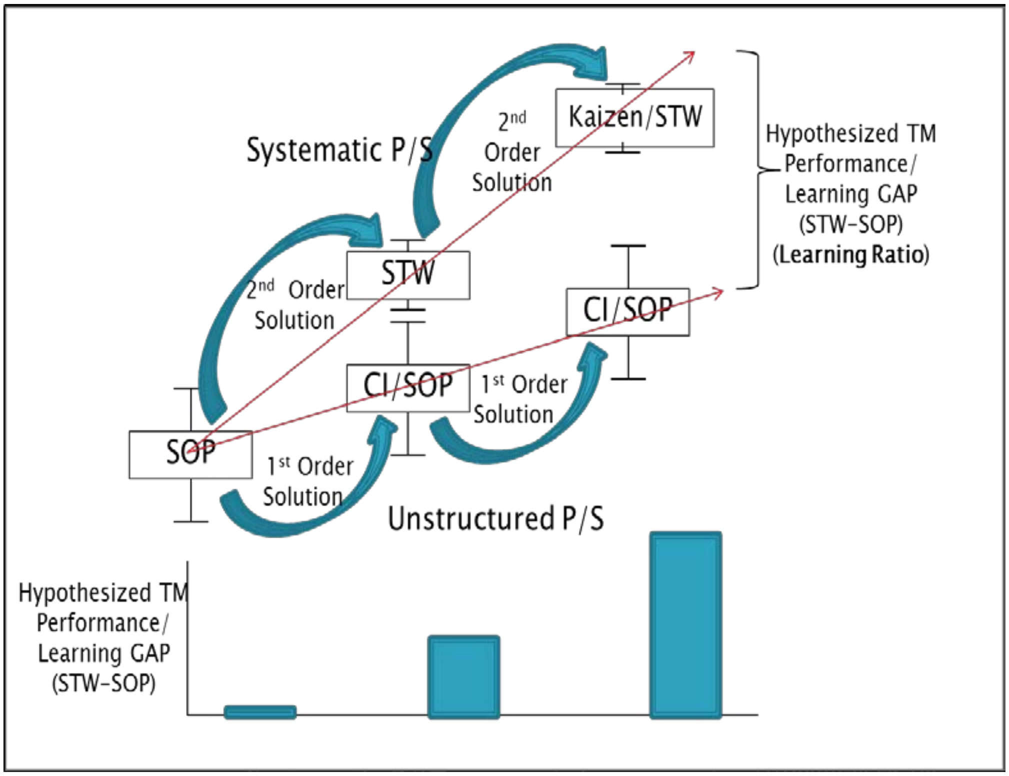


Figure 6.16 (originally 1.2). Conceptual illustration of part of the problem addressed in the proposed dissertation.

The third trend observed in the results was the tendency of operators (team members) in the treated teams to exhibit increased similarity in their learning rates or LCC results as their teams progressed through R3 and R4 compared to their untreated counterparts. This trend can be seen in terms of contextual LCCs in Figure 6.17 which shows the percent difference between the contextual LCC results for both operators in the treated and untreated groups and in Figure 6.18 for the TPT LCC results.

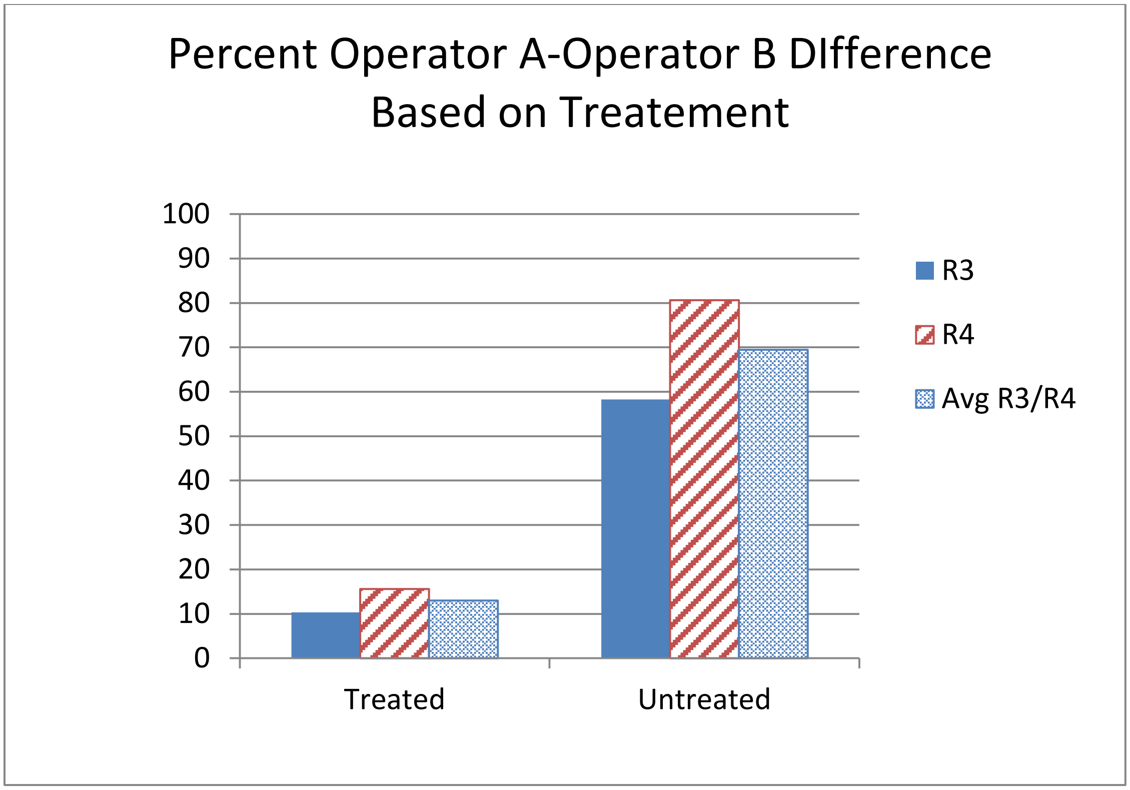


Figure 6.17 (originally 5.29). Percent operator to operator differences for R3, R4 and average R3 and R4 combined results.

Cycle time performance of each team was evaluated using the total cycle time (TCT) and TPT values to obtain wait times (WT) for both the treated and untreated teams. The analysis centered on the TPT and WT results since those are the measures most directly related to performance in this study. The difference in average TPT between the treated and untreated teams shown in Figure 6.19 illustrates the occurrence of continually increasing performance improvement going from R1/R2 to R3 and R4 for the treated teams compared to their untreated counterparts. As seen in Figure 6.20 this difference increases form about 10% for the baseline in R1/R2 to 20% in R3 up to nearly 30% in R4.

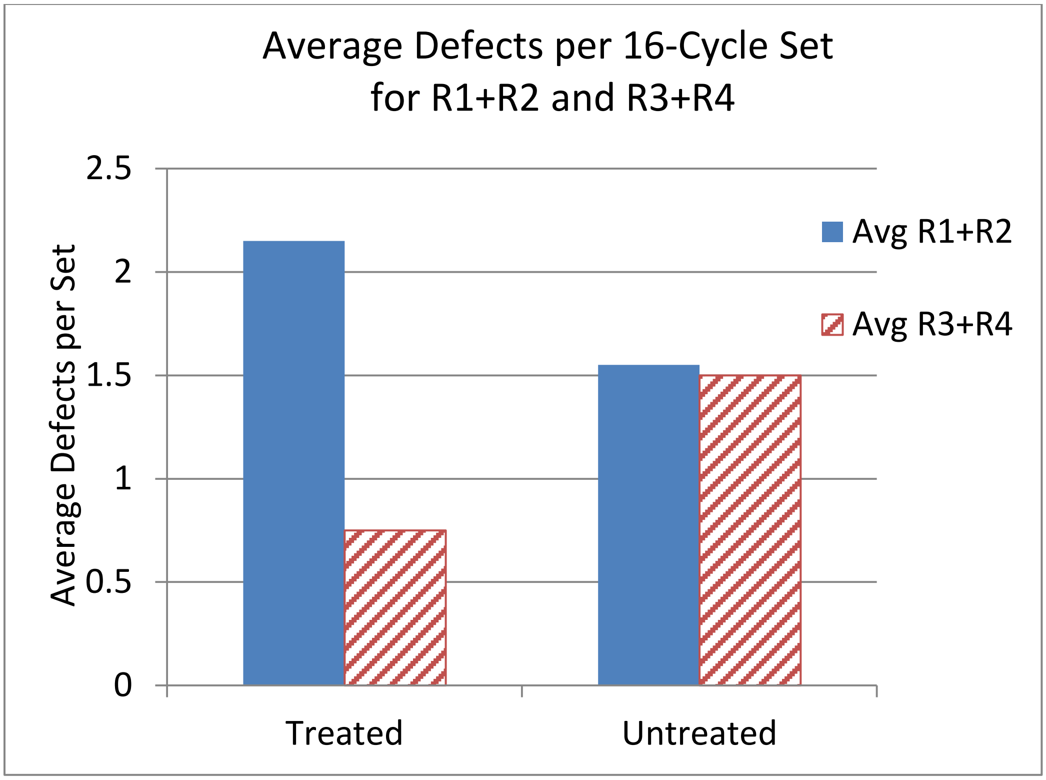


Figure 6.18 (originally 5.57). Average defect rate change for baseline (R1/R2) to treatment runs (R3/R4)

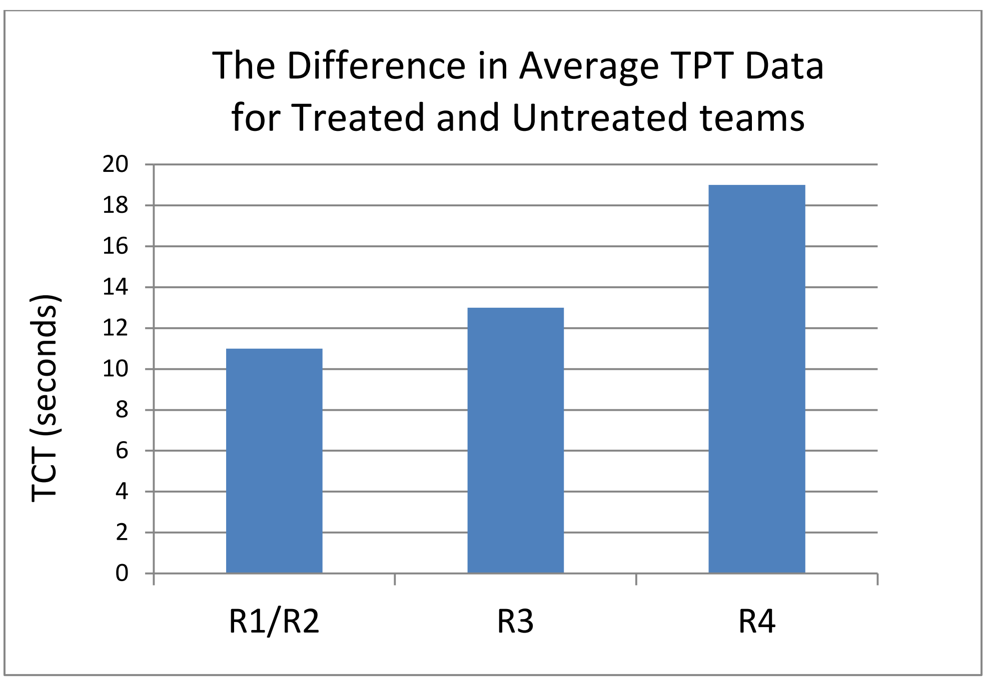
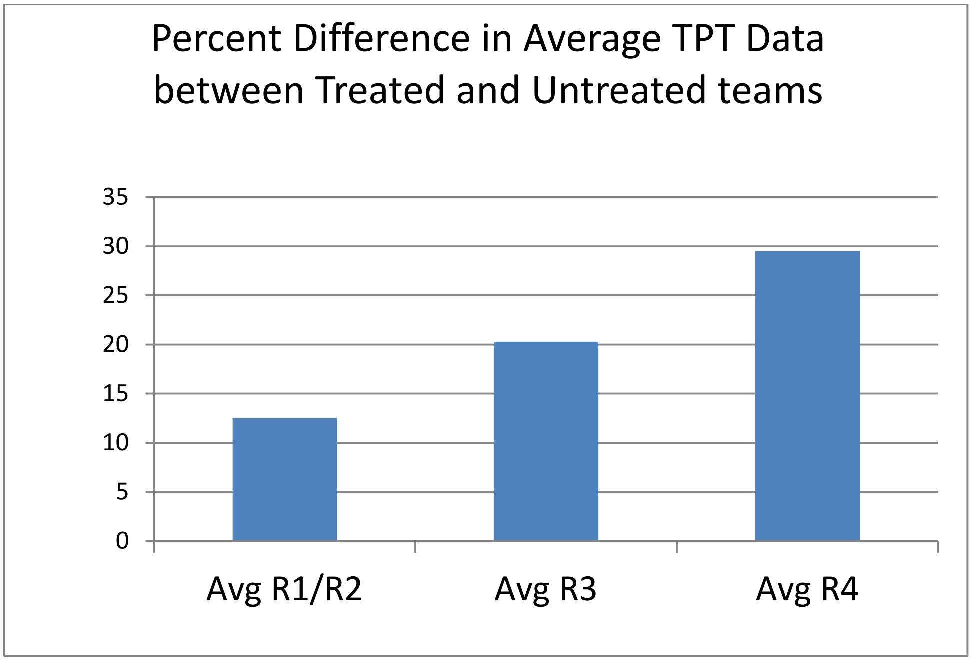


Figure 6.19 (originally 5.47). The difference in average untreated and treated TPT data from R1/R2, R3 and R4.



Figurer 6.20 (originally 5.47b). The percent difference in average TPT between treated and untreated teams.

The WT results help illustrate the effect of the treatment on the important ability of team members to synchronize their work. Figure 6.21 shows the difference in the total average WT per cycle experienced by both treated and untreated teams. The results indicate the WT for treated teams reduced from about 18 seconds in the baseline runs (R1/R2) to 15 seconds in R3 and finally to about 4 seconds during R4. This is contrasted by the data from the untreated teams showing an initial average WT of 25 seconds, which is reduced to about 17 seconds in R3 but remains about the same for R4.

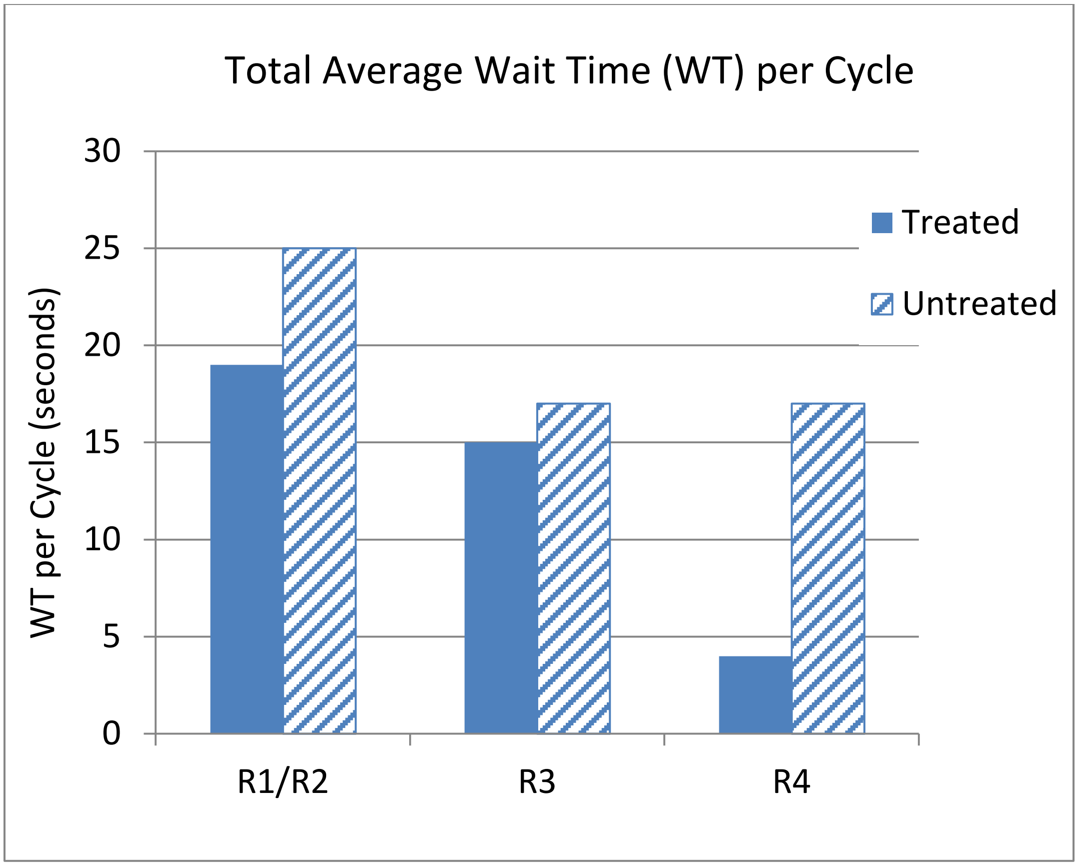


Figure 6.21 (originally 5.41). The average WT determined from the TCT and TPT values presented in Table 5.33 and 5.35.

CHAPTER 7: CONCLUSION AND SUGGESTED FUTURE RESEARCH FOR SUSTAINABLE CONTINUOUS IMPROVEMENT

The results of this study have shown the three null hypotheses proposed for this study to be invalid by demonstrating the effects of systematic problem solving to support Standardization (Variable 1) and to support waste elimination activities Vvariable 2) on individual team member learning and on the system (Operator A and Operator B combined. Showing there is an effect of these variables on team member learning and system performance enables the construction of a predictive probability model using the experimentally defined states for the framework to support the development of a continuous improvement capability with organizations. The application of the model will help provide a clear pathway for organizations wishing to develop systems capable of sustaining continuous improvement activities.

In addition, The learning curve results and analysis have established the occurrence of induced autonomous learning, determined experimentally derived learning ratios (LRs), and identified three major trends based on the learning curve coefficients derived from individual, contextual and TPT learning curves. The first trend seen consistently in the results is that the treated teams which are conducting systematic problem solving to eliminate abnormal work (following Standard work) in R3 exhibit higher LCC values on average than their untreated counterparts who were encouraged to identify and solve problems informally, and who did not require team members to follow Standard work procedures. This trend continued into R4 where the treated teams were taught formal forms of waste and used systematic problem solving to eliminate them as they occurred in their processes. Again the average LCC results from treated teams were higher than their untreated counterparts who continued with the same informal improvement methods they employed during R3.

The second major trend observed in all the average LCC results was the difference in the rate of decrease in learning rate experienced by the two groups. As each group progressed from the baseline runs (R1/R2) to R3 and R4, the rate of LCC decrease was observed to be more rapid for untreated teams then their treated counterparts. This results indicates to possibility of a continually widening gap between the outcomes of the treated and their untreated counterparts.

The third trend observed was the tendency of operators (team members) in the treated teams to exhibit increased similarity in their learning rates as their teams progressed through R3 and R4 compared to their untreated counterparts. This appears to support the existence of "maximum mutually shared knowledge" condition among treated team members which enables team members to take greater advantage of existing improvements to increase performance and improve synchronization of work, ultimately reducing lead time to the customer.

Another important observation of this study is the validation of the ability to improve quality as performance improves accompanied by a significant decrease in team member mental and physical burden.

Most importantly from an applications perspective is that this research identifies and validates the experimental conditions capable of producing enhanced learning rates among team members and to create opportunities to develop more robust and sustainable continuous improvement capabilities.

The experimental conditions studied represent perhaps the most critical operational components for creating a sustainable continuous improvement capacity based on an understanding of the most important fundamental principles of TPS, namely the need to establish Stable Standardized conditions *before* beginning to conduct Kaizen activities. Perhaps the most over-stated but under-performed operational component in TPS is *systematic* problem solving. As indicated in the introduction to the learning curve research section, problem solving tends to be taken for granted and is often overlooked as an intentional learning objective. The experience with studying Toyota has shown that one of the most critical differences observed between Toyota and other companies is the degree of *deliberateness* with which systematic problem solving is pursued throughout Toyota. Based on the results of this study, which has attempted to model basic conditions at the team member/work interface common to most processes, the application of systematic problem solving to support both Standardization then improvement (Kaizen) provides a significantly different and more robust dynamic learning environment for team members and ultimately the entire organization than the prevailing environment of most existing organizations. .

In some respects these results presented here represent a worst case scenario since all the operators were young and generally well-motivated to complete their 256-cycle requirement as quickly as possible so they could go home early. In many organizations, experienced operators have much less motivation to improve. That said even in organizations where strong motivation does exist, non-systematic improvements, exemplified in the untreated experimental conditions, may still give significant improvements, however, they can also create large knowledge gaps as seen in the difference between the treated and untreated average total CT results.

Finally, the purpose of the predictive model and assessment tool is to provide organizations with a realistic understanding of their current condition with respect to developing sustainable continuous improvement capabilities, and to provide a fundamental roadmap for continued development. It is my fervent hope this work proves helpful in some small way towards the development of more fundamentally benevolent systems capable of meeting the needs of the customer, the company, the workers and their communities.

7.1. Suggested Future Research

The learning curve studies conducted in this research represent a first step towards more comprehensive analysis of the critical factors effecting sustainable CI development. Suggestions for future LC research include, but are not limited to the following;

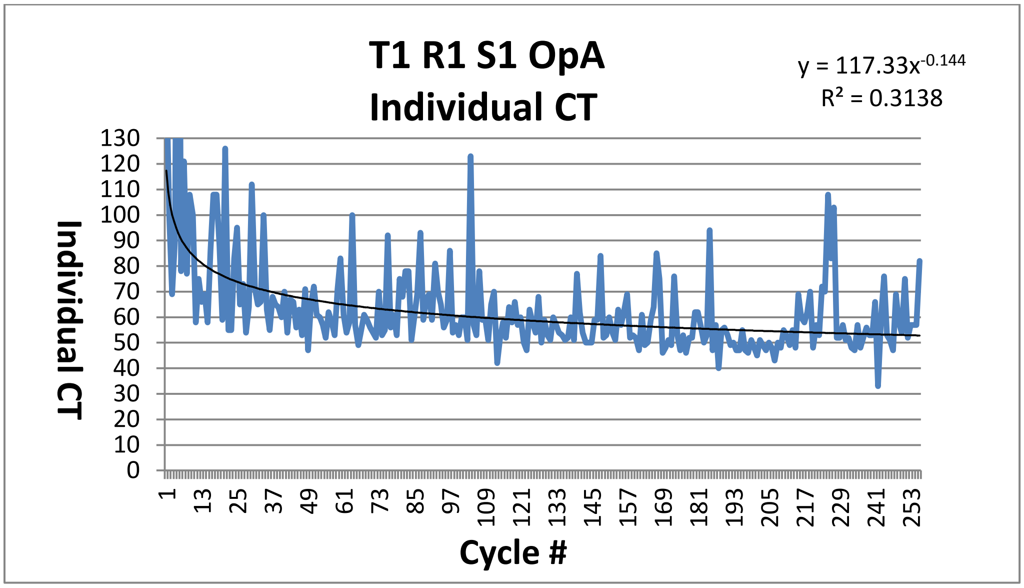
1. Evaluating the effect of Standard work and job rotation frequency on process performance using learning-forgetting learning curve models.
2. Replicating this study to gather more data for statistical analysis.
3. Applying the model to specific organizations and tracking their development over time.
4. Building the effects of management decisions on learning at the team member/work interface.
5. Conducting on-site assessments coupled with on-line assessments using the same basic tool and evaluating the resulting gap to identify organizational biases interfering with CI development.

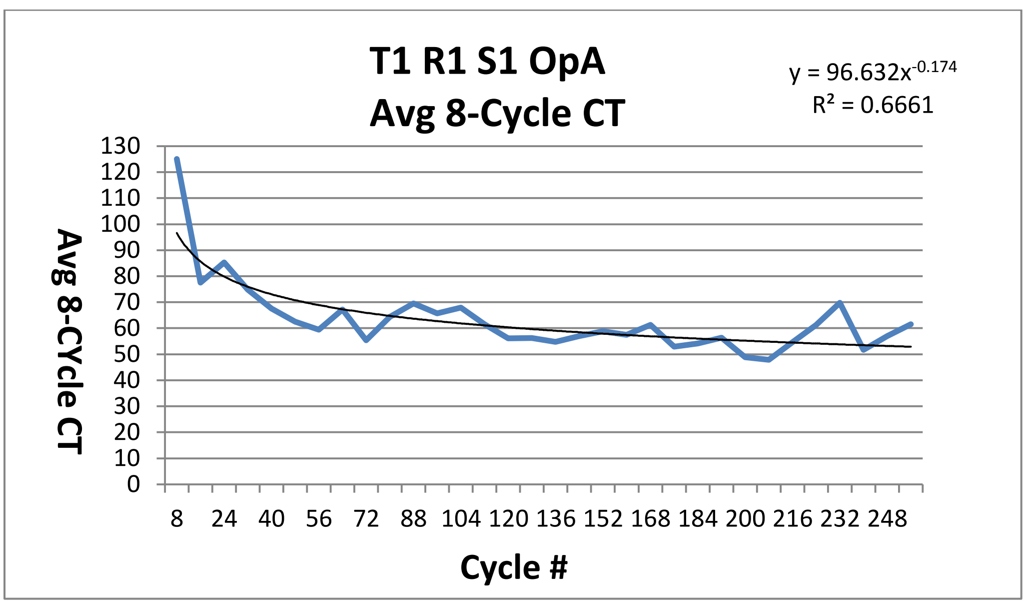
APPENDIX

Appendix A: 1-Cycle and 8-Cycle 256 Cycle Learning Curves from R1.

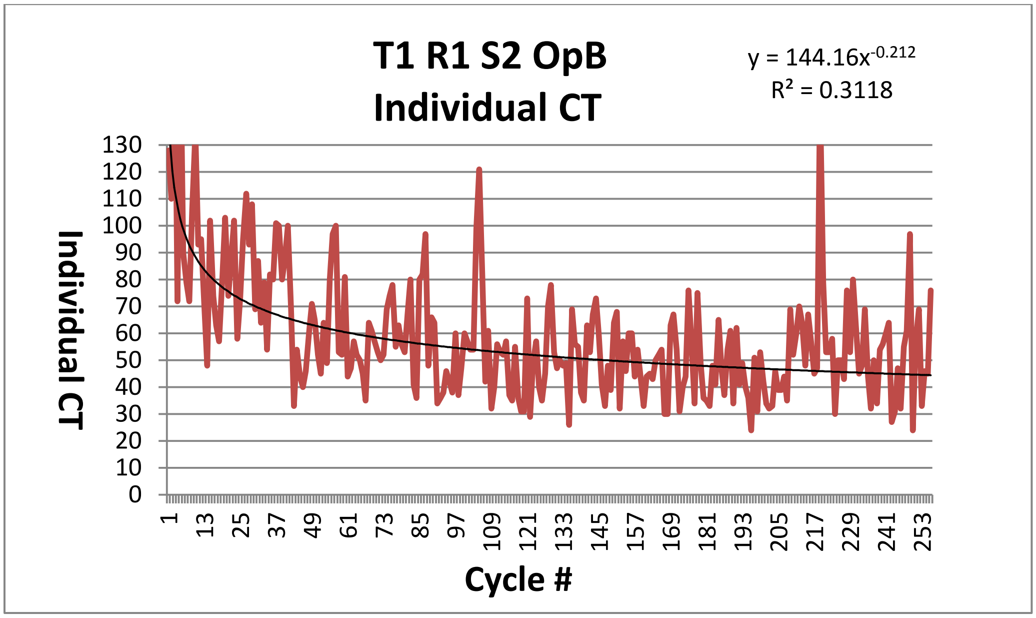
Team 1-R1

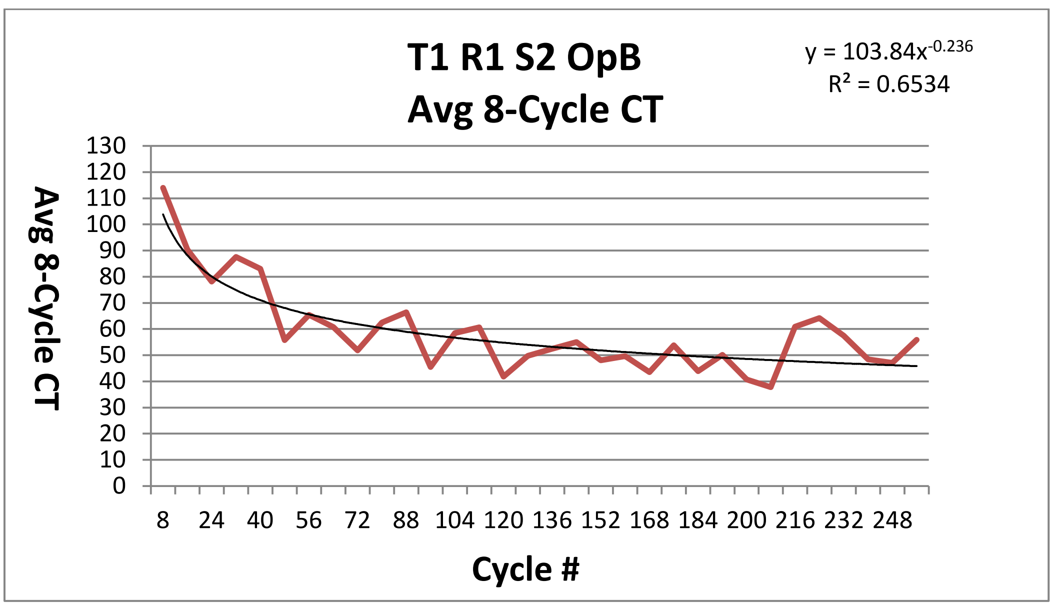
Station 1- Operator A





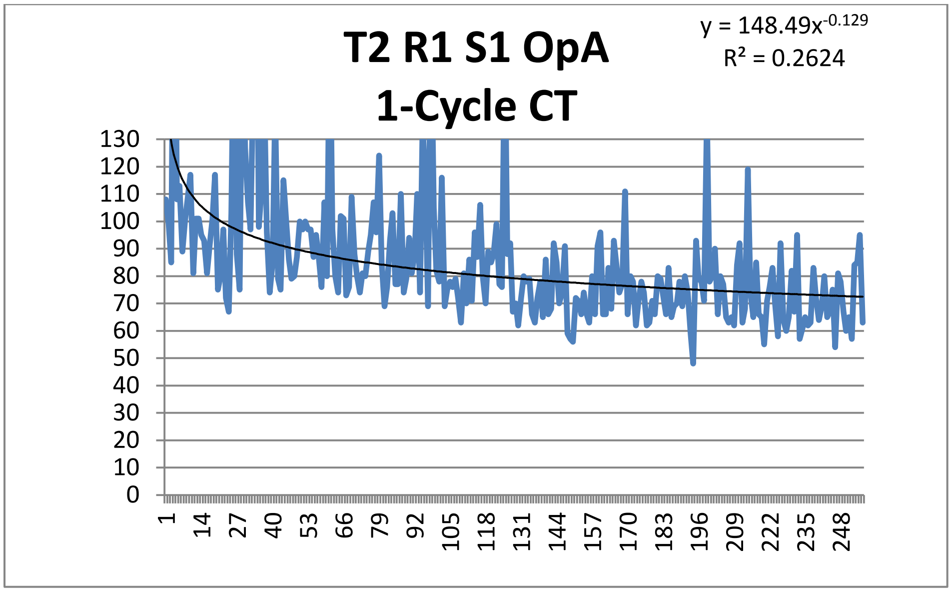
Station 2- Operator B

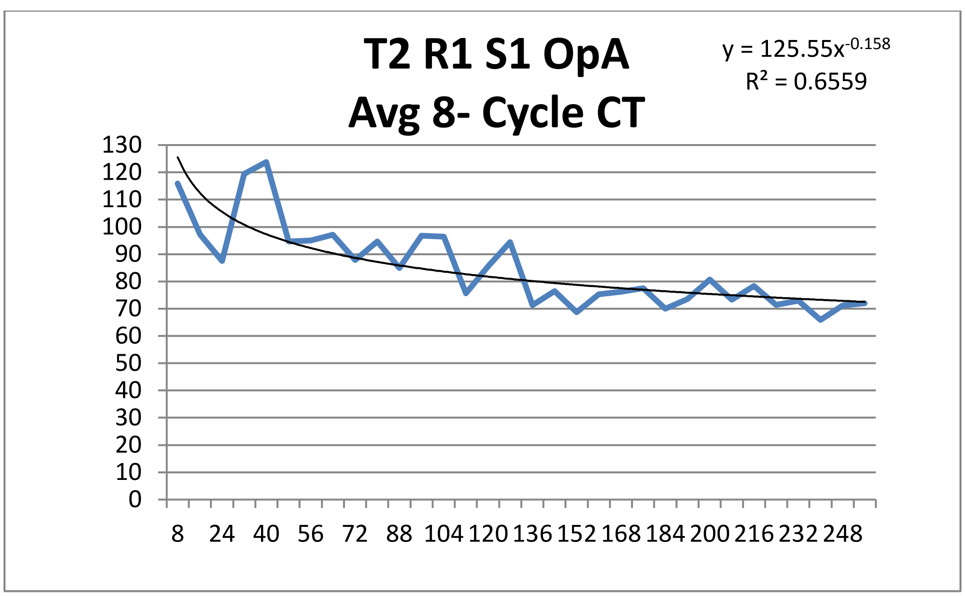




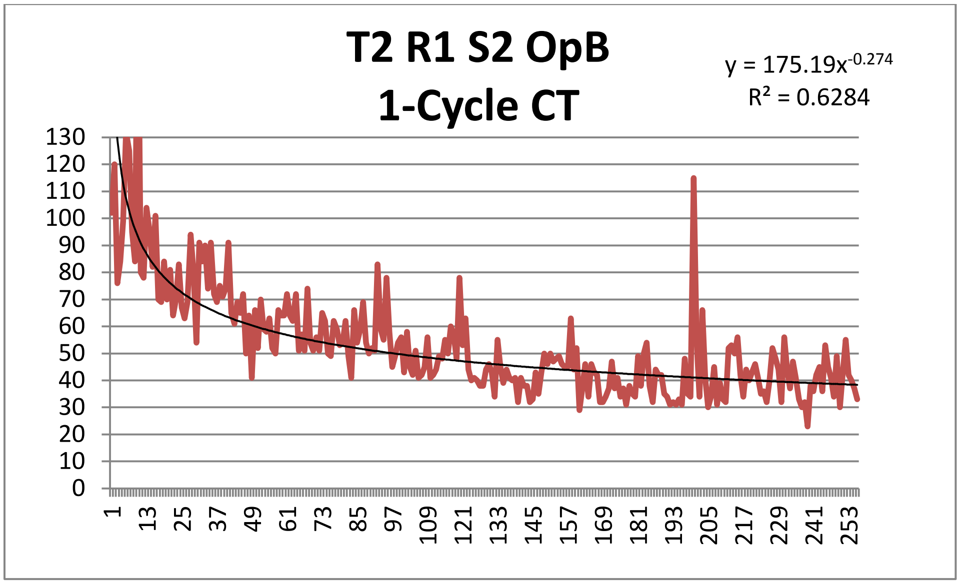
Team 2-R1

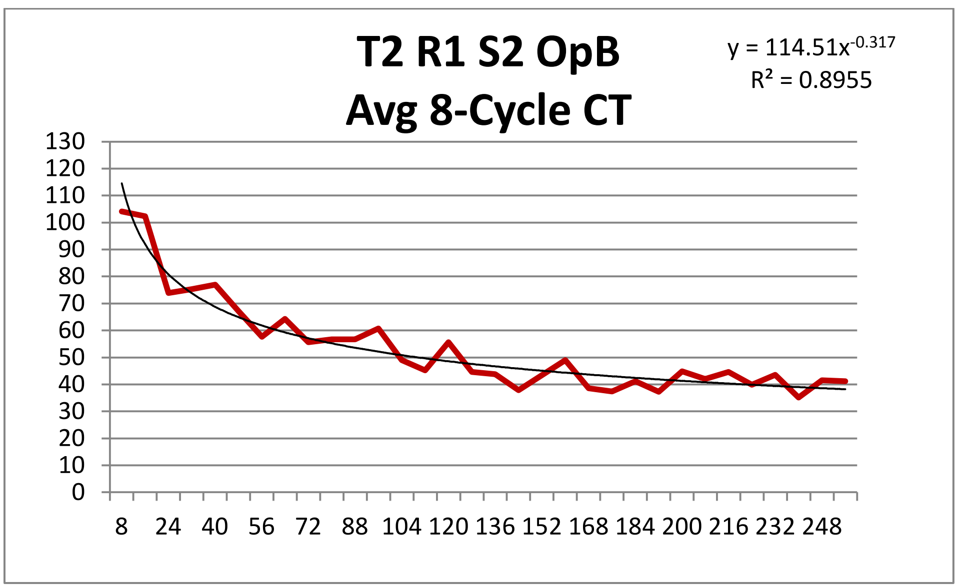
Station 1- Operator A





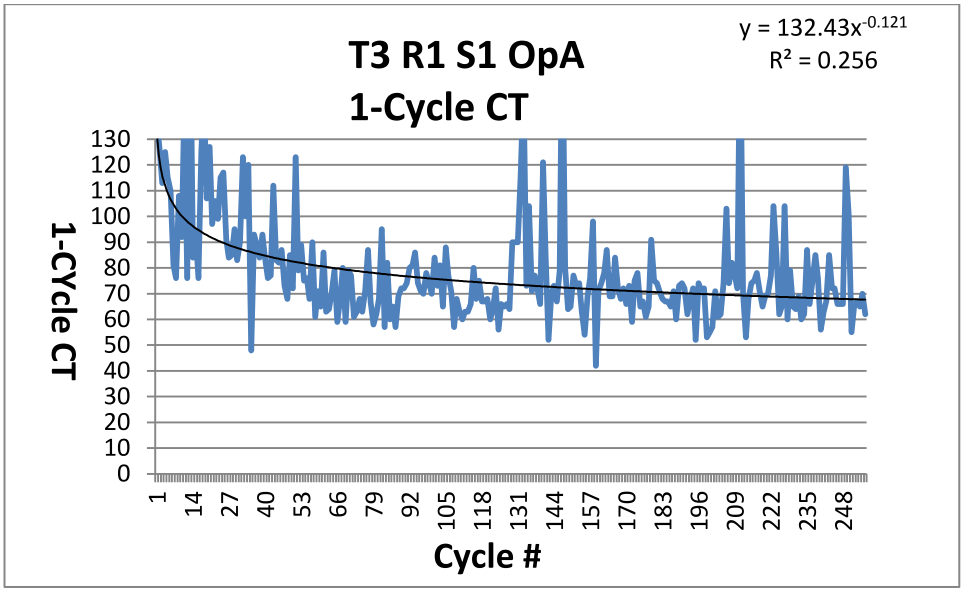
Station 2-Operator B

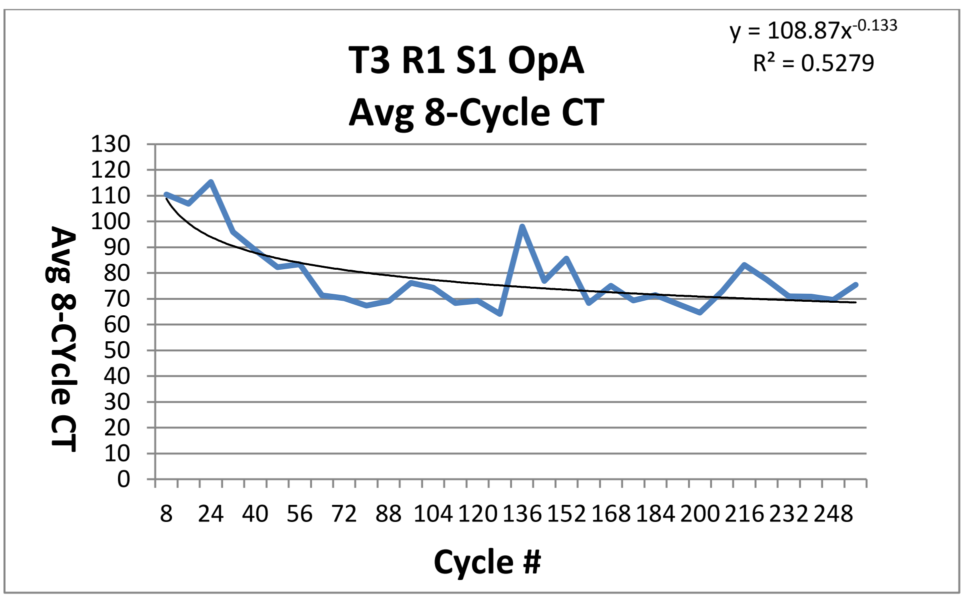




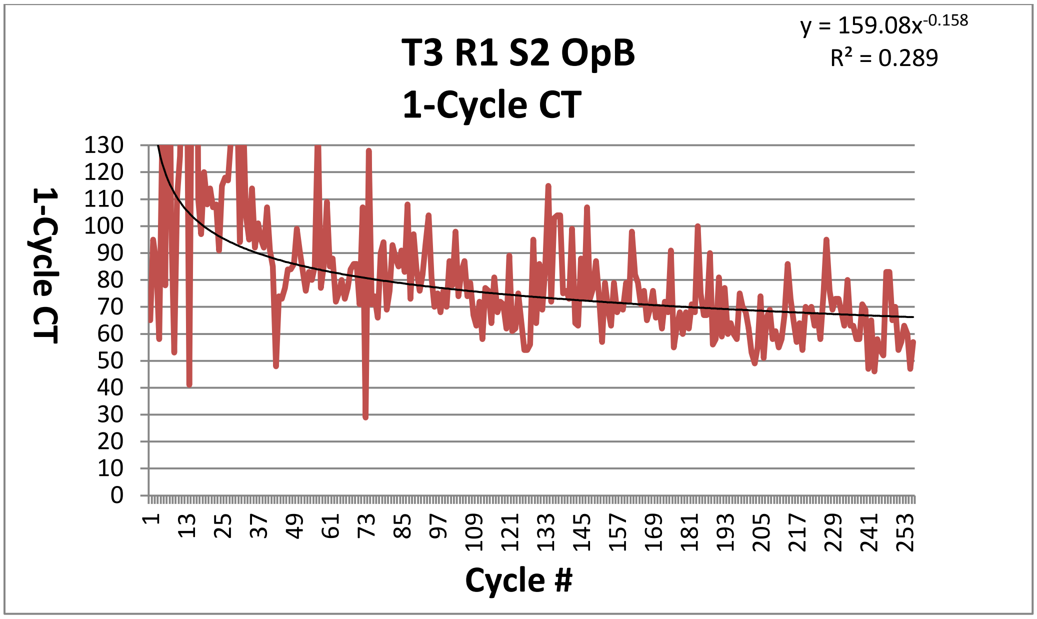
Team 3-R1

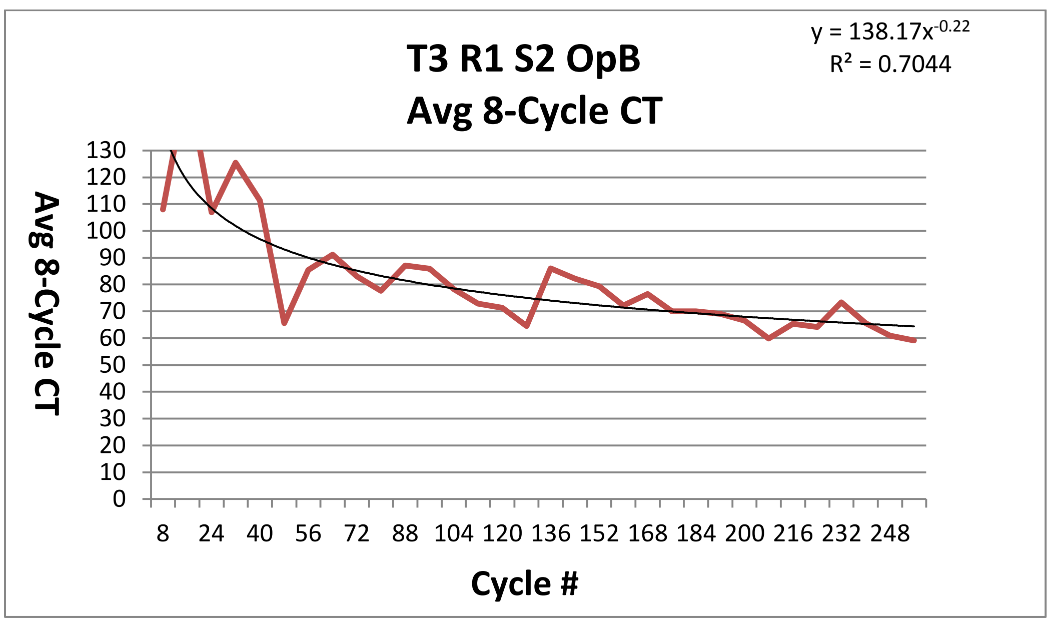
Station 1- Operator A





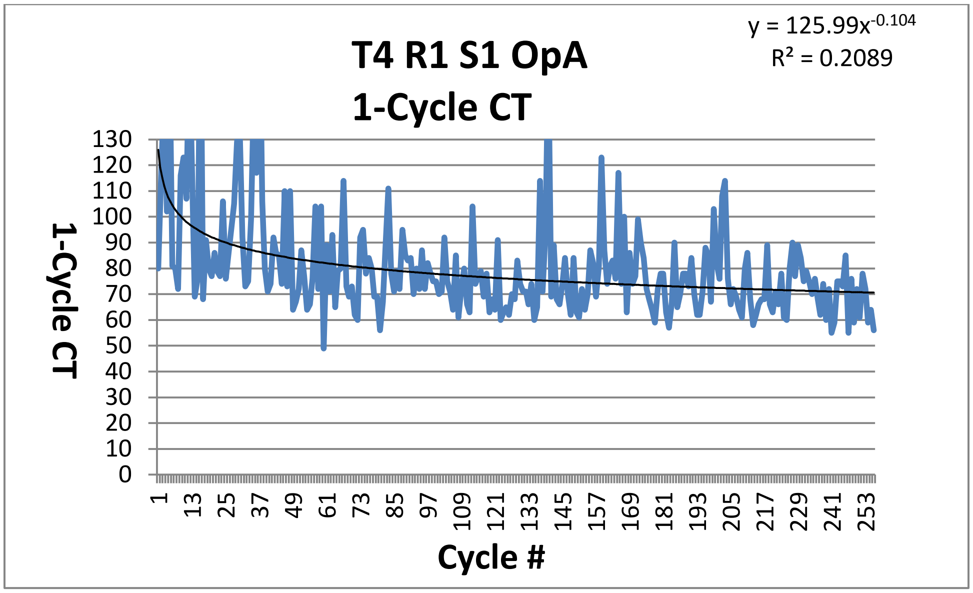
Station 2- Operator B

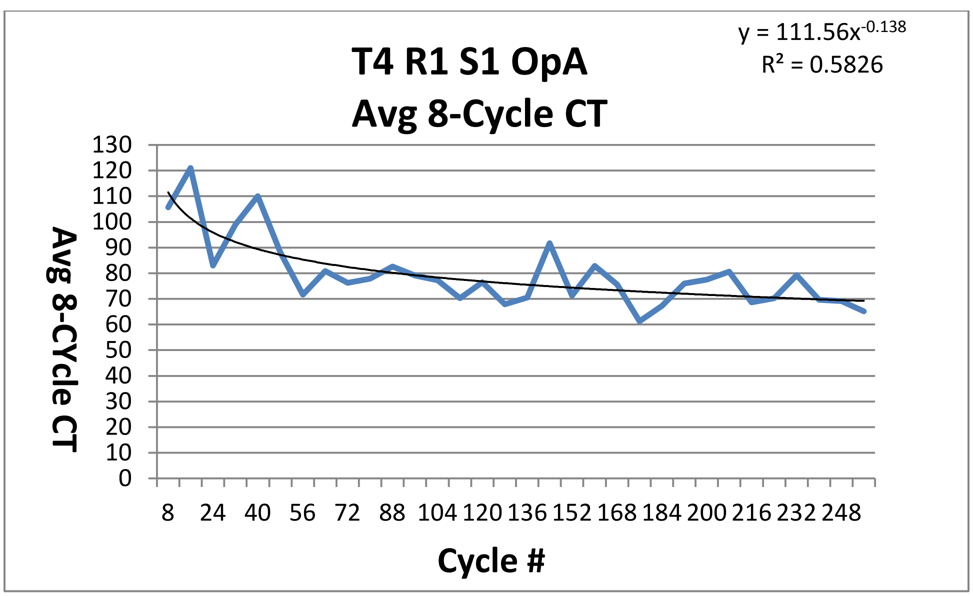




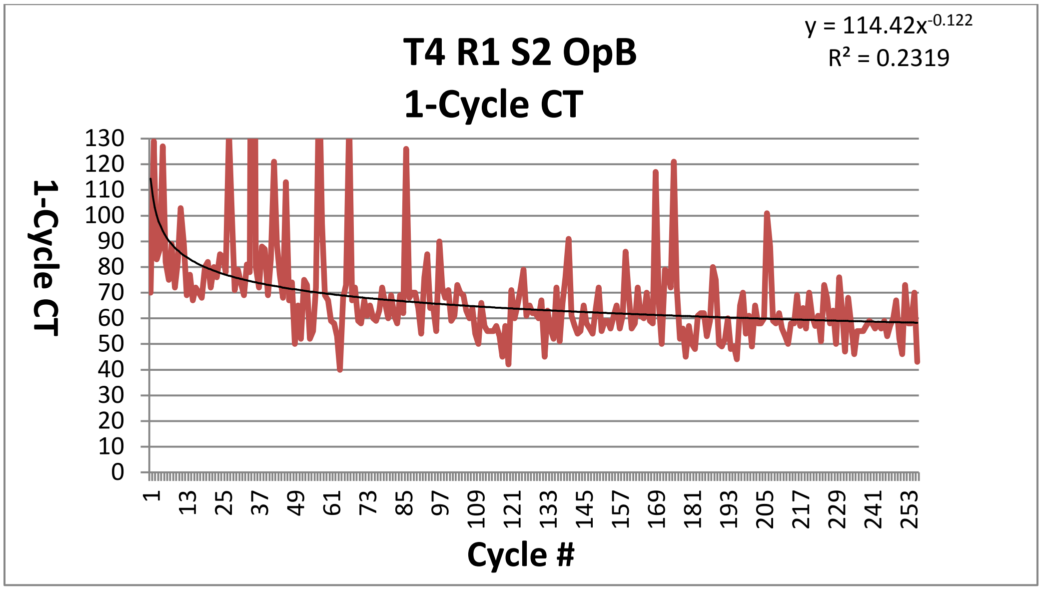
Team 4-R1

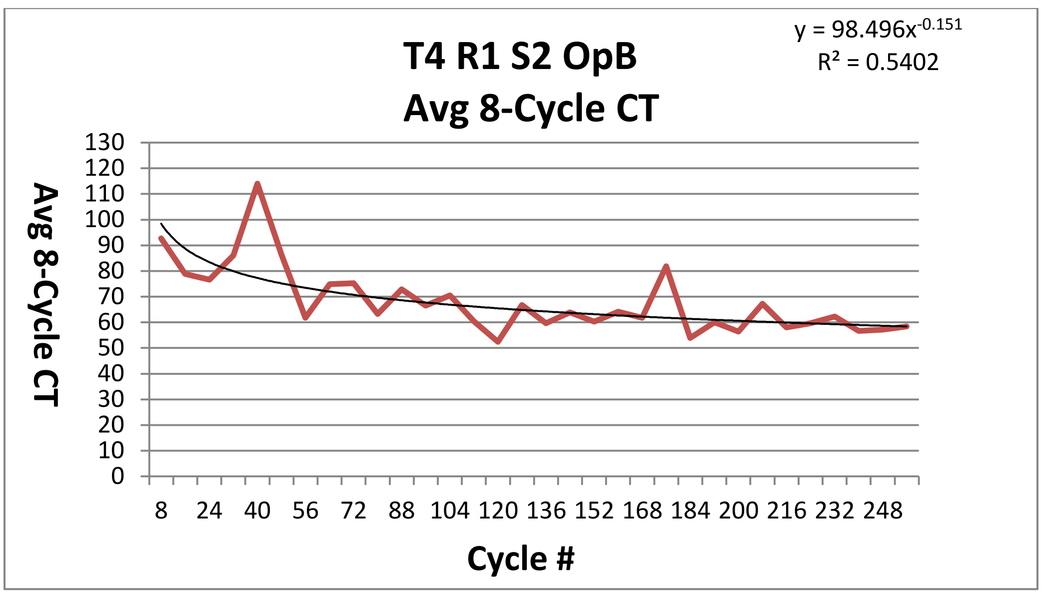
Station 1- Operator A





Station 2- Operator B

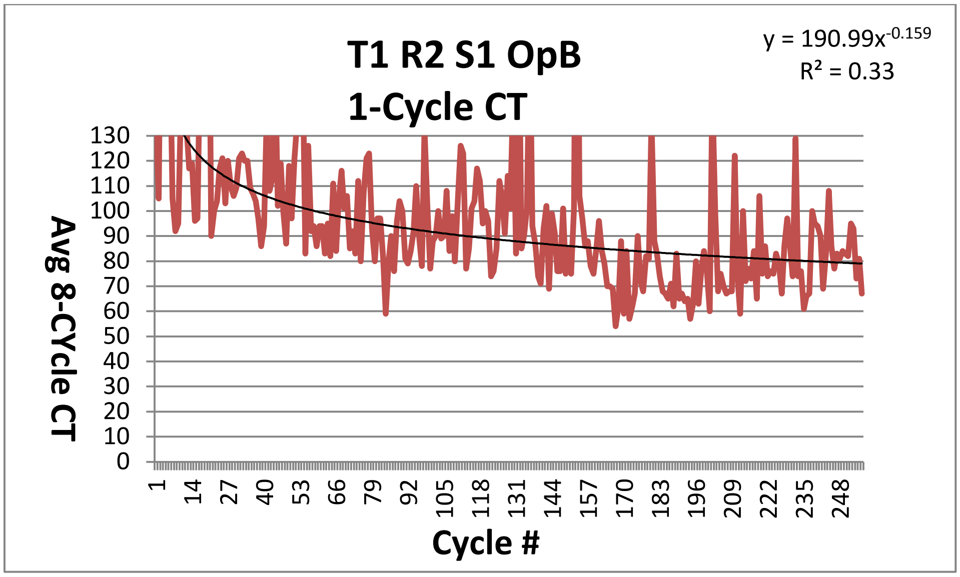


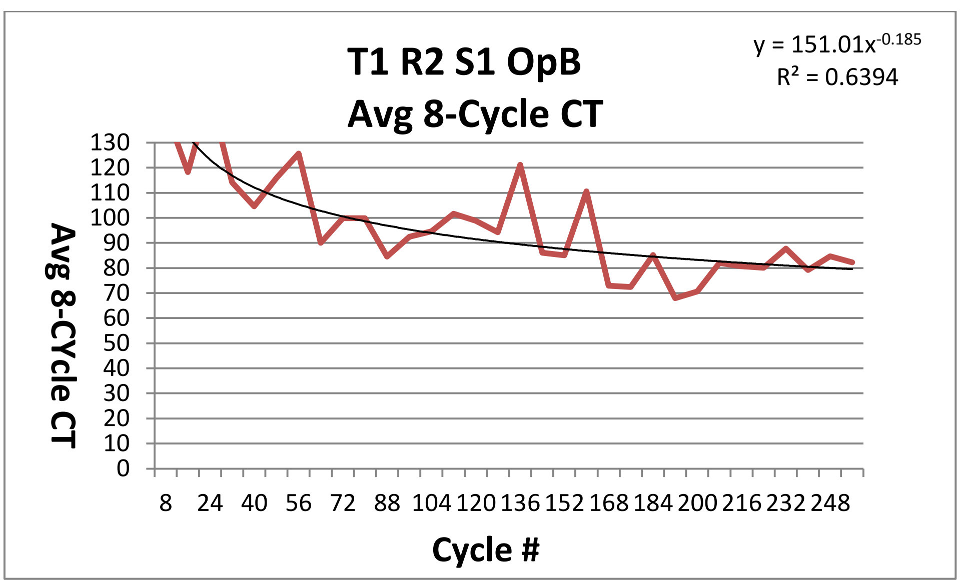


Appendix B: 1-Cycle and 8-Cycle 256 Cycle Learning Curves from R2

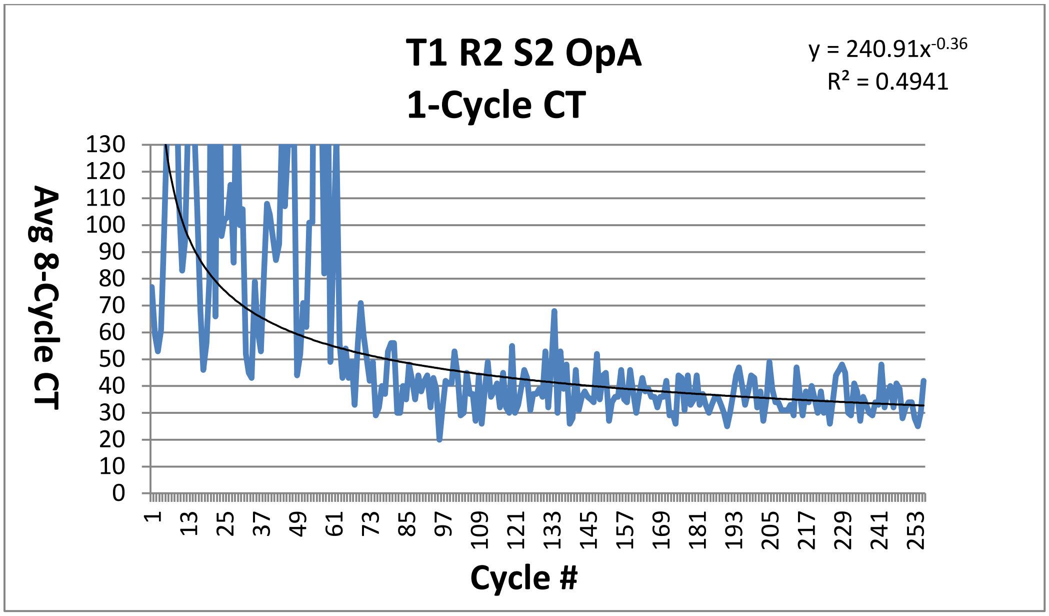
Team 1-R2

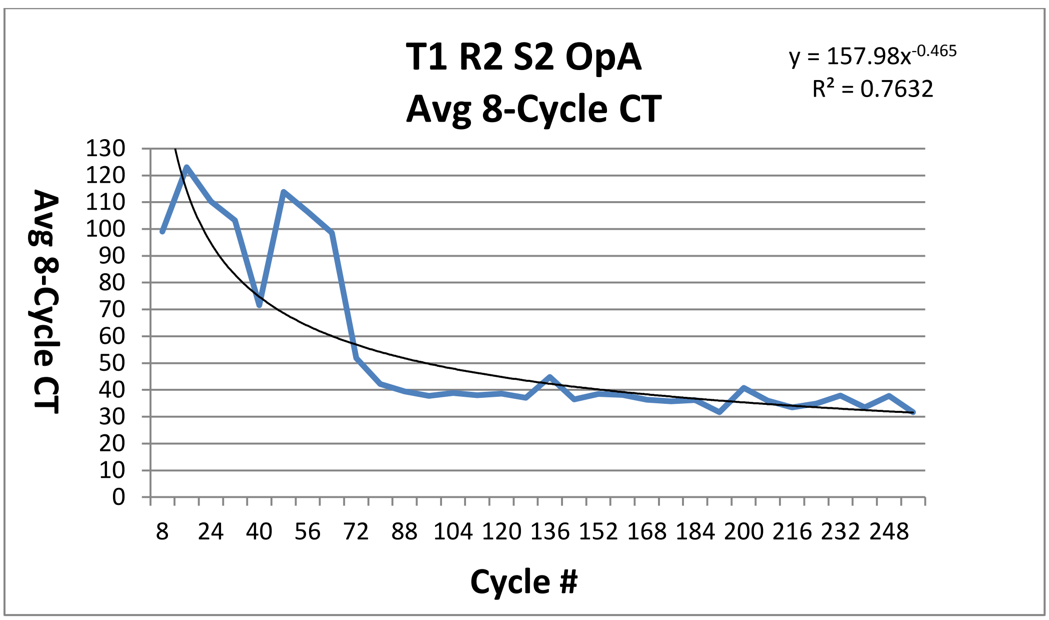
Station 1- Operator B





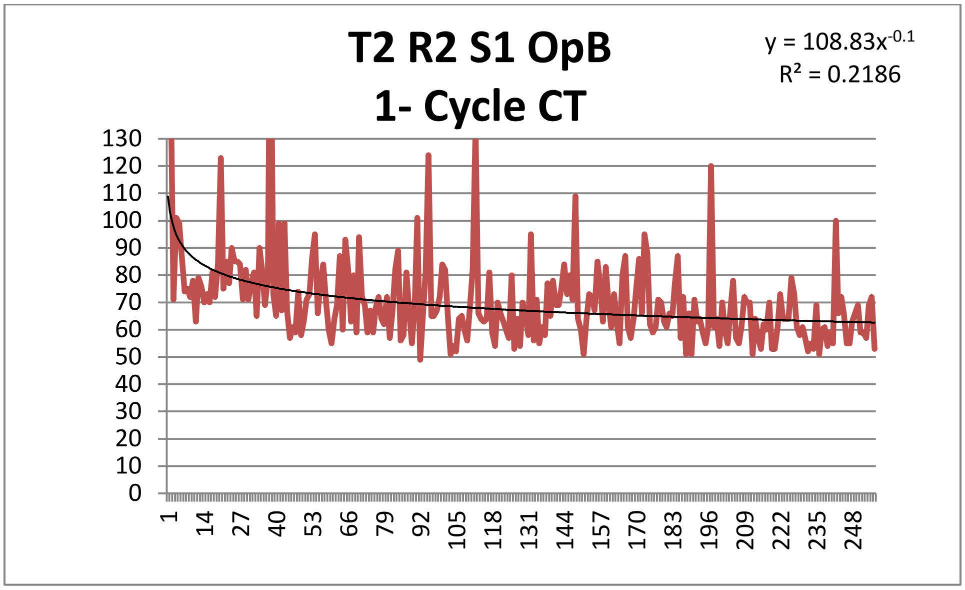
Station 2- Operator A

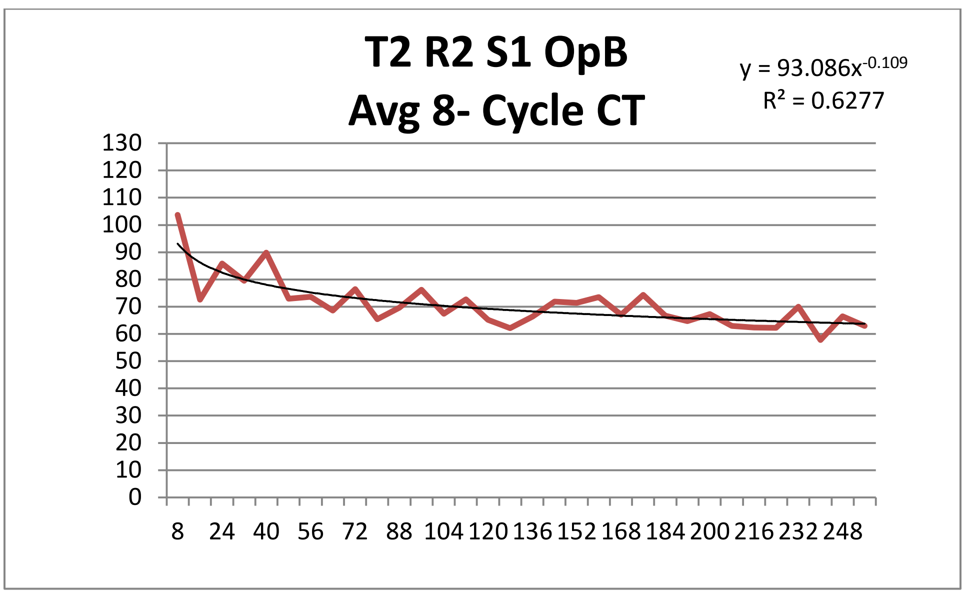




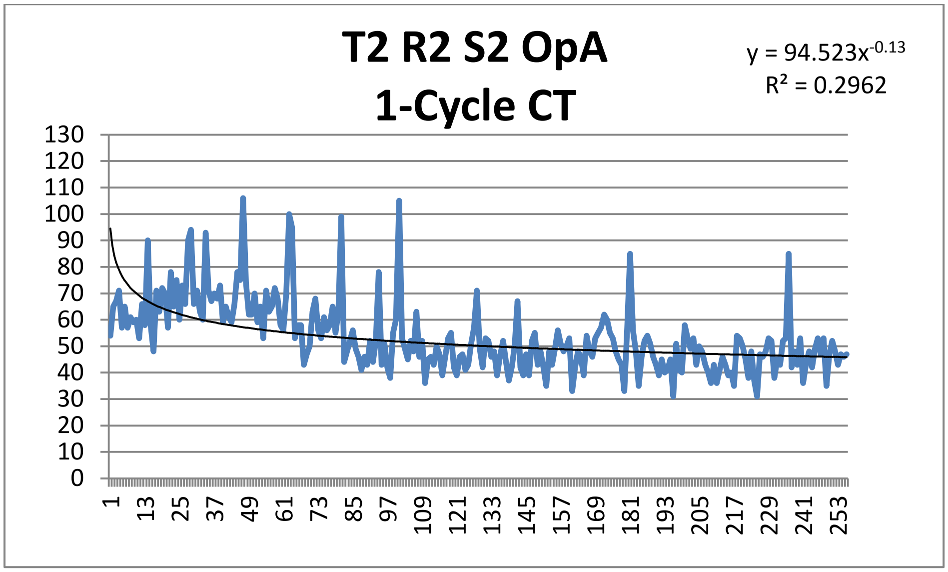
Team 2-R2

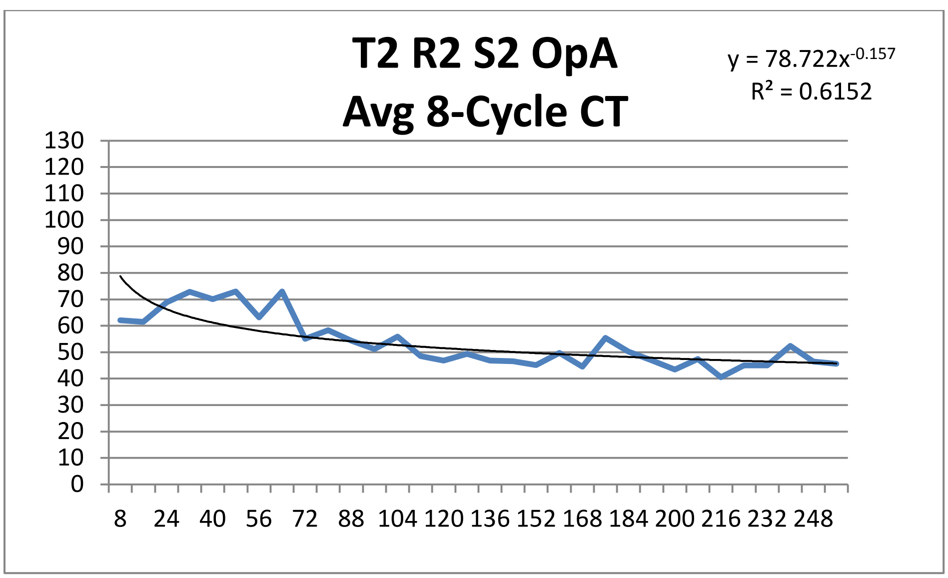
Station 1- Operator B





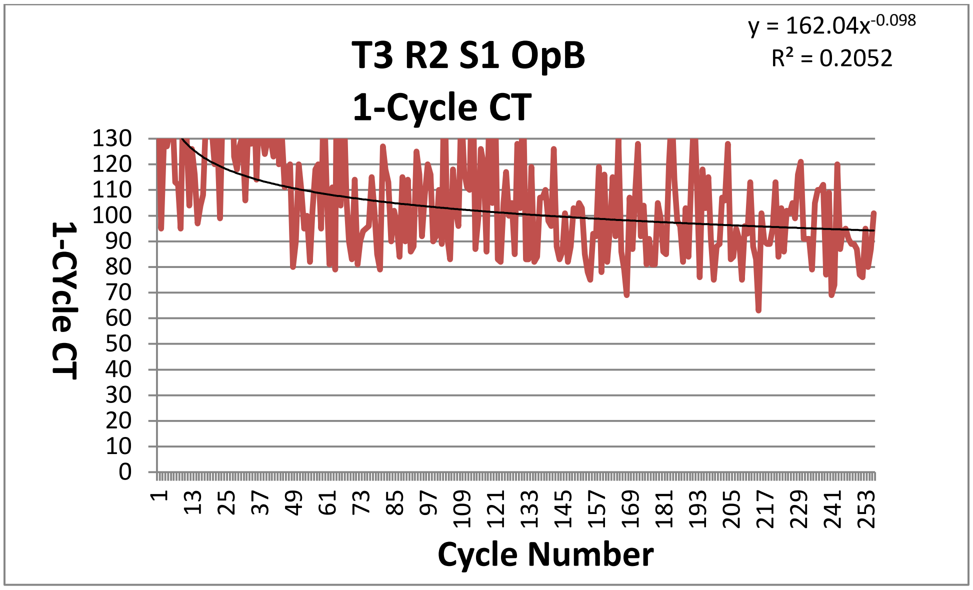
Station 2- Operator A

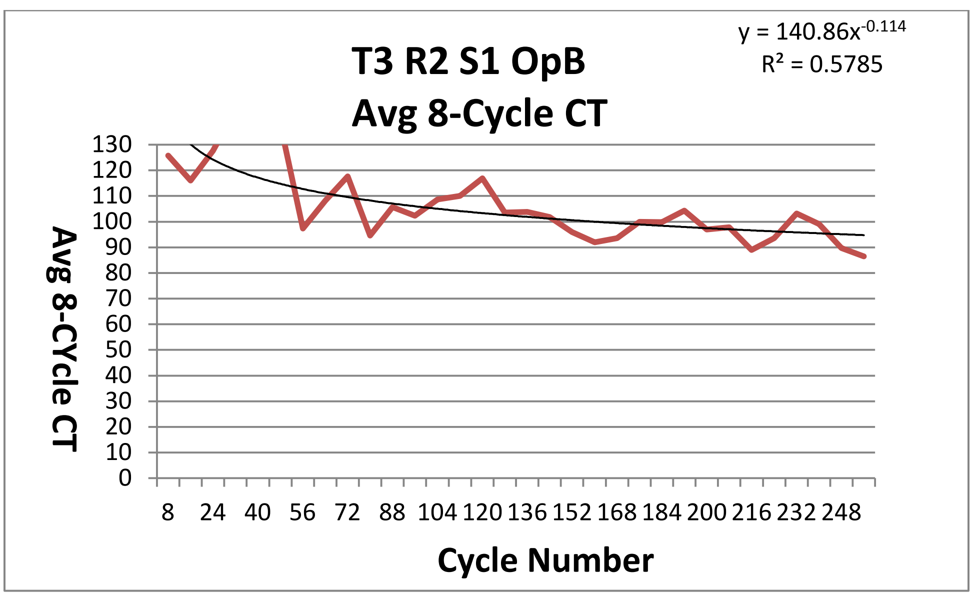




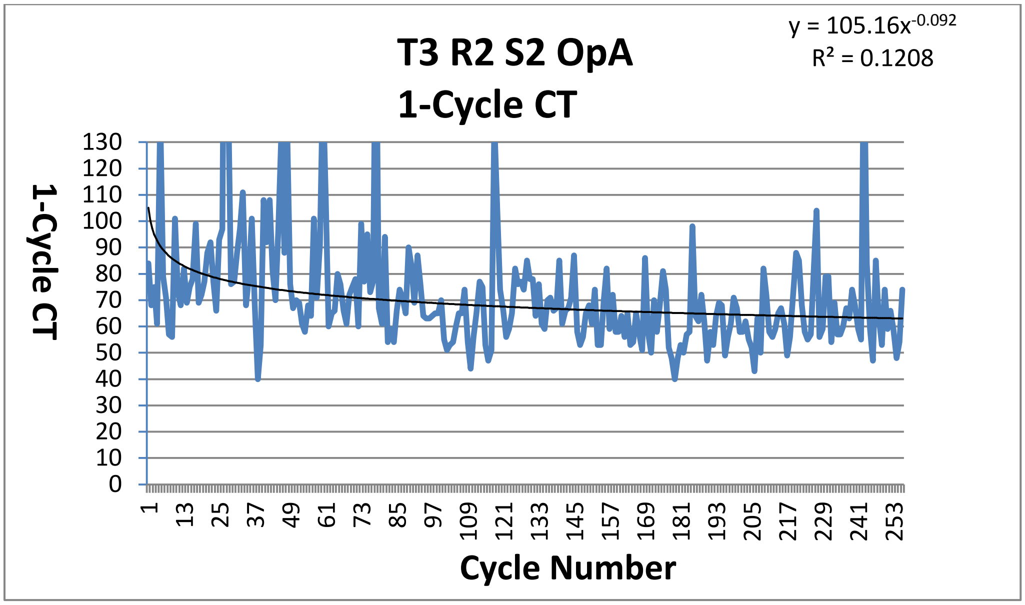
Team 3-R2

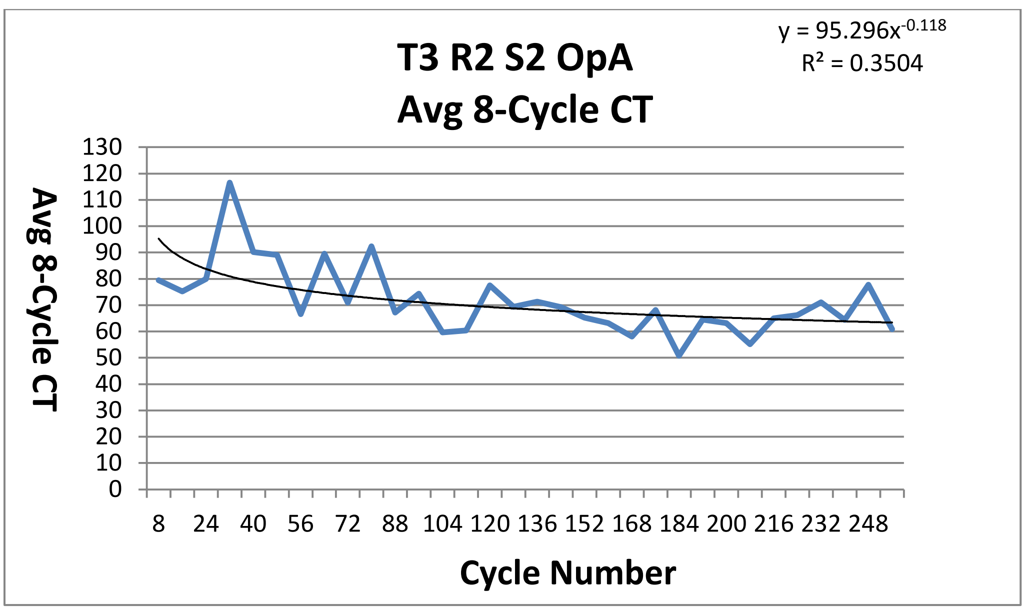
Station 1- Operator B





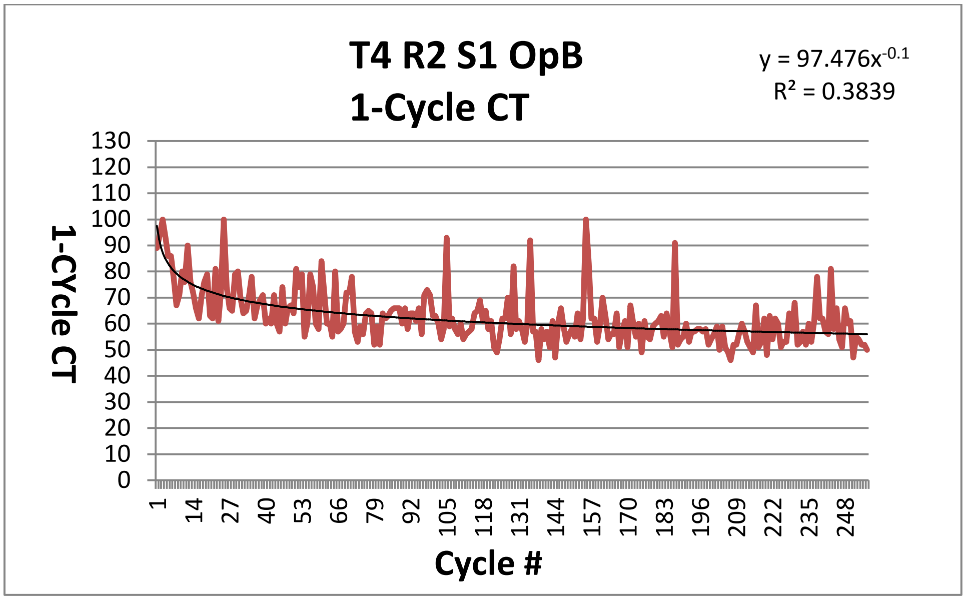
Station 2- Operator A

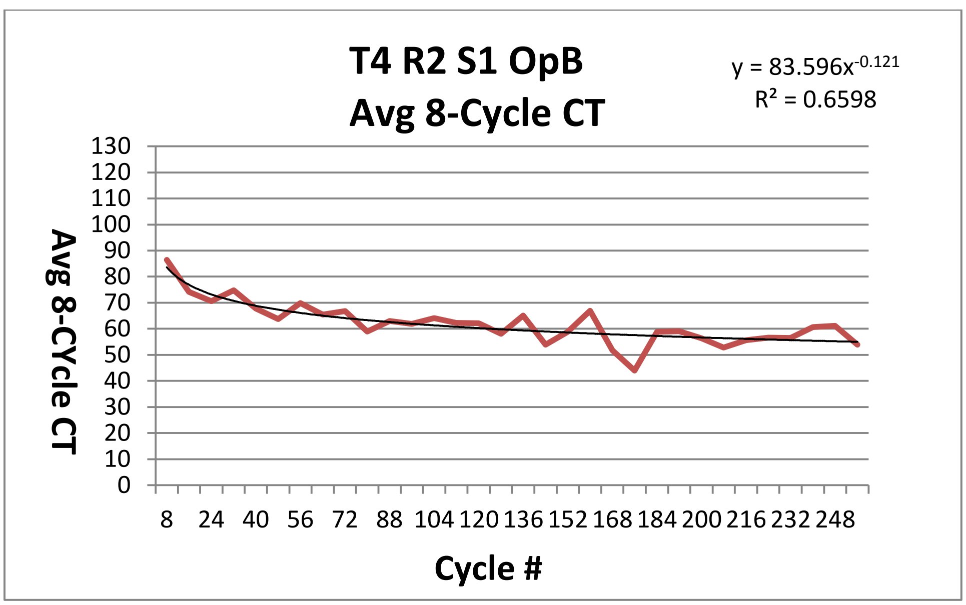




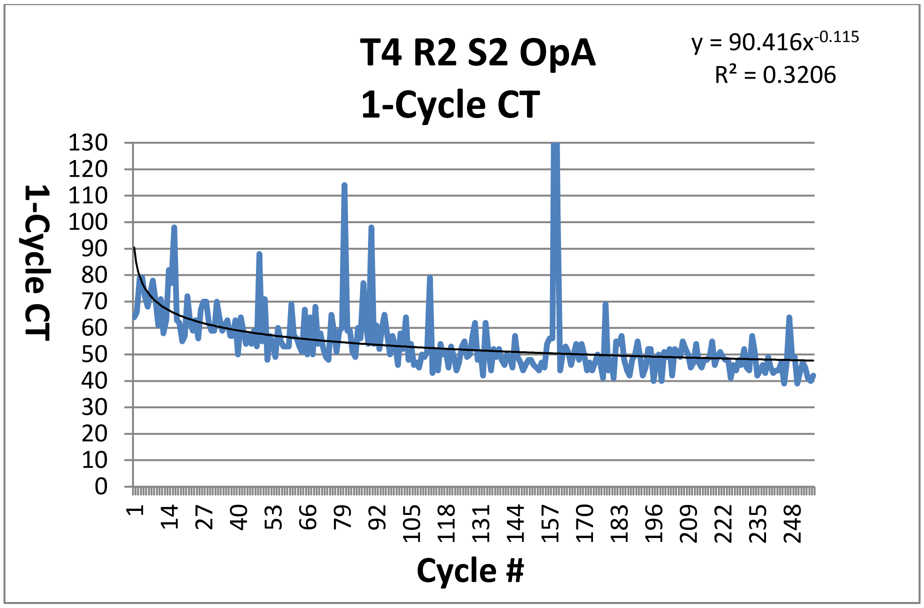
Team 4-R2

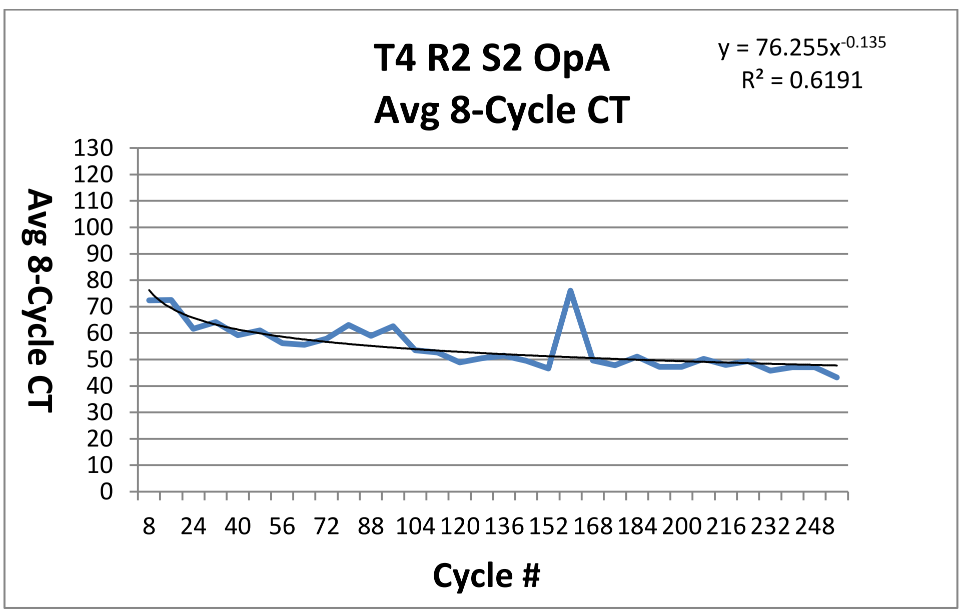
Station 1- Operator B





Station 2- Operator A


T4 R2 S2 OpA
1-Cycle CT
y = 90.416x^-0.115
R² = 0.3206
1-Cycle CT
Cycle #


T4 R2 S2 OpA
Avg 8-Cycle CT
y = 76.255x^-0.135
R² = 0.6191
Avg 8-Cycle CT
Cycle #

Appendix C: R1 & R2 Station-Specific Paired t-test

Untreated vs Treated Group using 8-Cycle 256 and 128-Cycle Data Sets

t-Test: Two-Sample Assuming Equal Variances

256-Cycle R1/R2 Station 1	*Untreated (T1&2)*	*Treated (T1&4)*
Mean	-0.1285	-0.1545
Variance	0.000494	0.000902
Observations	4	4
Pooled Variance	0.000698	
Hypothesized Mean Difference	0	
df	6	
t Stat	1.392081	
P(T<=t) two-tail	0.213306	
t Critical two-tail	2.446912	

R1/R2 Two-Sided t-test results using 256-cycle Station 1 average LCC results

t-Test: Two-Sample Assuming Equal Variances

256-Cycle R1/R2 Station 2	*Untreated (T2&3)*	*Treated (T1&4)*
Mean	-0.203	-0.24675
Variance	0.007542	0.023135
Observations	4	4
Pooled Variance	0.015338	
Hypothesized Mean Difference	0	
df	6	
t Stat	0.499577	
P(T<=t) two-tail	0.635161	
t Critical two-tail	2.446912	

R1/R2 Two-Sided t-test results using 256-cycle Station 2 average LCC results

t-Test: Two-Sample Assuming Equal Variances

128-Cycle R1/R2 Station 1	*Untreated (T2&3)*	*Treated (T1&4)*
Mean	-0.04025	-0.04073
Variance	0.000896	0.002266
Observations	4	4
Pooled Variance	0.001581	
Hypothesized Mean Difference	0	
df	6	
t Stat	0.016893	
P(T<=t) two-tail	0.987069	
t Critical two-tail	2.446912	

R1/R2 Two-Sided t-test results using 128- cycle Station 1 average LCC results

t-Test: Two-Sample Assuming Equal Variances

128-Cycle R1/R2 Station 2	*Untreated (T2&3)*	*Treated (T1&4)*
Mean	-0.04175	-0.03633
Variance	0.003093	0.001119
Observations	4	4
Pooled Variance	0.002106	
Hypothesized Mean Difference	0	
df	6	
t Stat	-0.16719	
P(T<=t) two-tail	0.872714	
t Critical two-tail	2.446912	

R1/R2 Two-Sided t-test results using 128-cycle Station 2 average LCC results

Appendix D: R1 & R2 Operator-Specific Paired t-test

Untreated vs Treated Group using 256 and 128-Cycle Data Sets

t-Test: Two-Sample Assuming Equal Variances

256-Cycle Operator A R1/R2	*Untreated (T2&3)*	*Treated (T1&4)*
Mean	-0.1415	-0.228
Variance	0.000379	0.025278
Observations	4	4
Pooled Variance	0.012829	
Hypothesized Mean Difference	0	
df	6	
t Stat	1.080048	
P(T<=t) two-tail	0.321611	
t Critical two-tail	2.446912	

R1/R2 Two-Sided t-test results using 256-cycle Operator A average LCC results

t-Test: Two-Sample Assuming Equal Variances

256-Cycle Operator B R1/R2	*Untreated (T2&3)*	*Treated (T1&4)*
Mean	-0.19	-0.17325
Variance	0.009789	0.002434
Observations	4	4
Pooled Variance	0.006111	
Hypothesized Mean Difference	0	
df	6	
t Stat	-0.30302	
P(T<=t) two-tail	0.772107	
t Critical two-tail	2.446912	

R1/R2 Two-Sided t-test results using 256-cycle Operator B average LCC results

t-Test: Two-Sample Assuming Equal Variances

128-Cycle Operator A R1/R2	*Untreated (T2&3)*	*Treated (T1&4)*
Mean	-0.02725	-0.03948
Variance	0.001162	0.001125
Observations	4	4
Pooled Variance	0.001144	
Hypothesized Mean Difference	0	
df	6	
t Stat	0.511263	
P(T<=t) two-tail	0.62743	
t Critical two-tail	2.446912	

R1/R2 Two-sided t-test results using 128-cycle Operator A average LCC results

t-Test: Two-Sample Assuming Equal Variances

128-Cycle Operator B R1/R2	*Untreated (T2&3)*	*Treated (T1&4)*
Mean	-0.05475	-0.03758
Variance	0.002324	0.002271
Observations	4	4
Pooled Variance	0.002297	
Hypothesized Mean Difference	0	
df	6	
t Stat	-0.50675	
P(T<=t) two-tail	0.630409	
t Critical two-tail	2.446912	

R1/R2 Two-sided t-test results using 128-cycle Operator B average LCC results

Appendix E: R1 & R2 Station-Specific and Operator-Specific Paired t-Test

256-Cycle versus 128-Cycle Data Sets

t-Test: Paired Two Sample for Means

Station 1 R1/R2	*256-Cycles*	*128-Cycles*
Mean	-0.1415	-0.04049
Variance	0.000791	0.001355
Observations	8	8
Pearson Correlation	0.113781	
Hypothesized Mean Difference	0	
df	7	
t Stat	-6.53591	
P(T<=t) two-tail	0.000323	
t Critical two-tail	2.364624	

R1/R2 Paired t-test results using combined operator A and B LCC results for Station 1

t-Test: Paired Two Sample for Means

Station 2 R1/R2	*256-Cycles*	*128-Cycles*
Mean	-0.22488	-0.03904
Variance	0.013694	0.001813
Observations	8	8
Pearson Correlation	0.246149	
Hypothesized Mean Difference	0	
df	7	
t Stat	-4.60047	
P(T<=t) two-tail	0.002483	
t Critical two-tail	2.364624	

R1/R2 Paired t-test results using combined operator A and B LCC results for Station 2

t-Test: Paired Two Sample for Means

Operator A R1/R2	*256-Cycles*	*128-Cycles*
Mean	-0.157375	-0.0333625
Variance	0.00149341	0.00102285
Observations	8	8
Pearson Correlation	-0.39773076	
Hypothesized Mean Difference	0	
df	7	
t Stat	-5.92943872	
P(T<=t) two-tail	0.00058196	
t Critical two-tail	2.36462425	

R1/R2 Paired t-test results using combined Station 1 and 2 LCC results for operator A

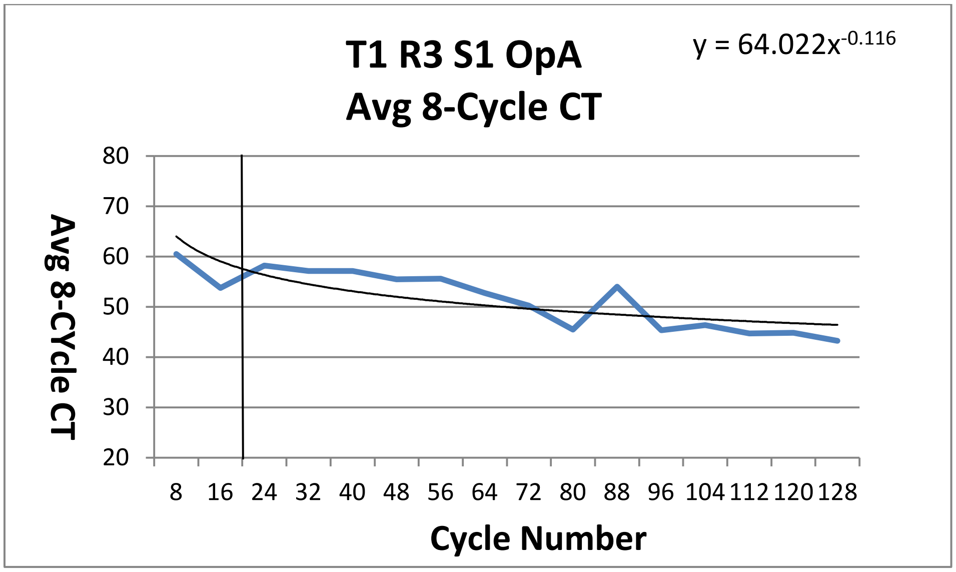
t-Test: Paired Two Sample for Means

Operator B R1/R2	*256-Cycles*	*128-Cycles*
Mean	-0.181625	-0.0461625
Variance	0.00531827	0.00205347
Observations	8	8
Pearson Correlation	-0.02084977	
Hypothesized Mean Difference	0	
df	7	
t Stat	-4.42137568	
P(T<=t) two-tail	0.00307616	
t Critical two-tail	2.36462425	

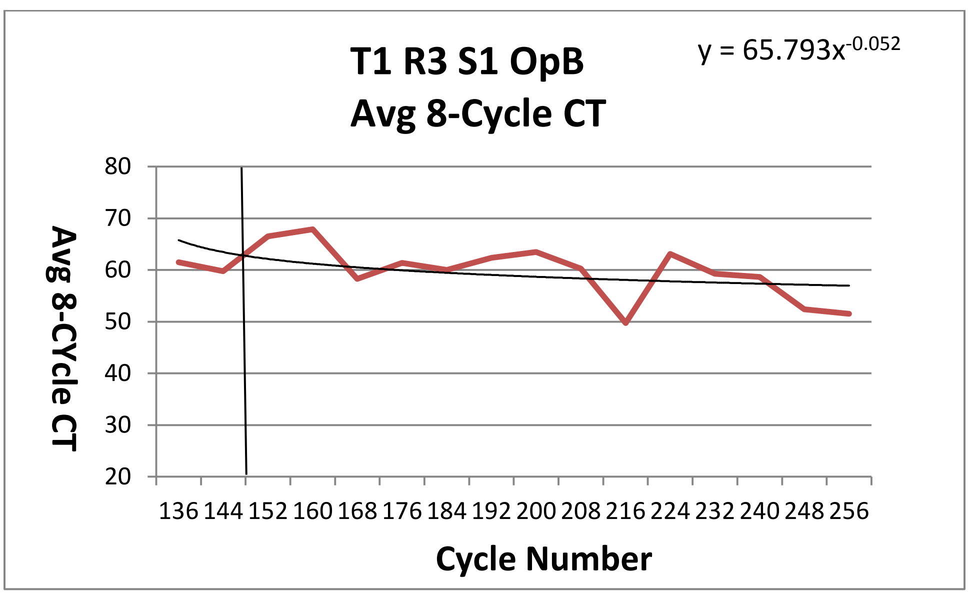
R1/R2 Paired t-test results using combined Station 1 and 2 LCC results for operator B

Appendix F: 128-Cycle Learning Curves with 16-Cycle Marker

Team 1-Station 1-R3

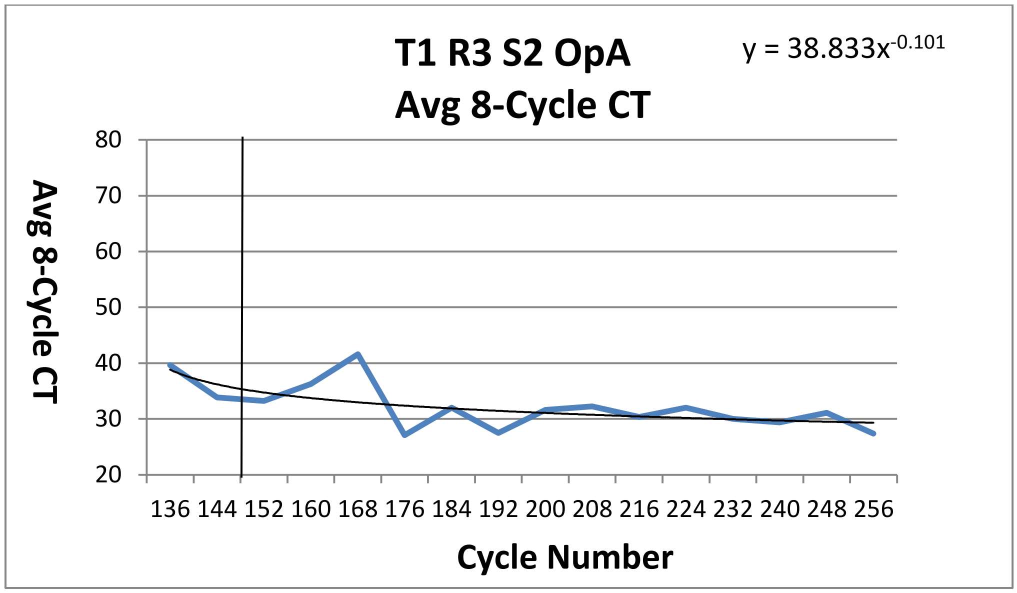


Team 1, Operator A, Station 1 Learning Curve w/ line at cycle 16 and power equation showing LCC

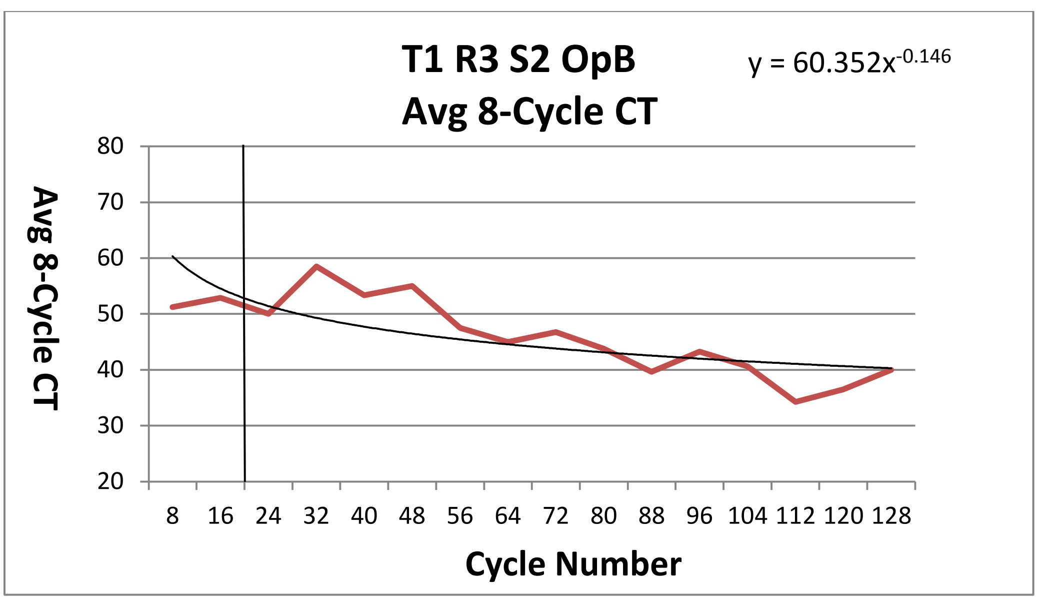


Team 1, Operator B, Station 1 Learning Curve w/ line at cycle 16 and power equation showing LCC

Team 1-Station 2-R3

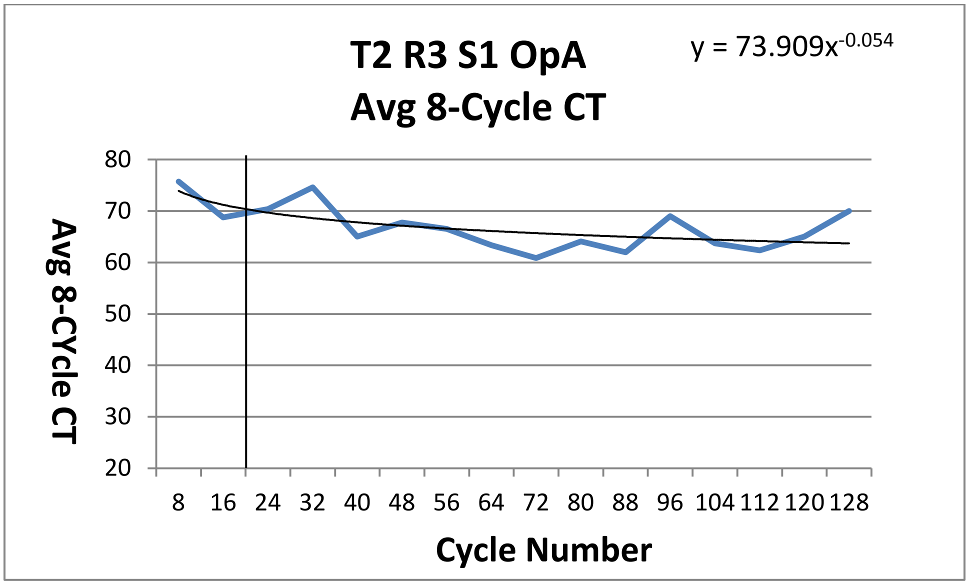


Team 1, Operator A, Station 2 Learning Curve w/ line at cycle 16 and power equation showing LCC

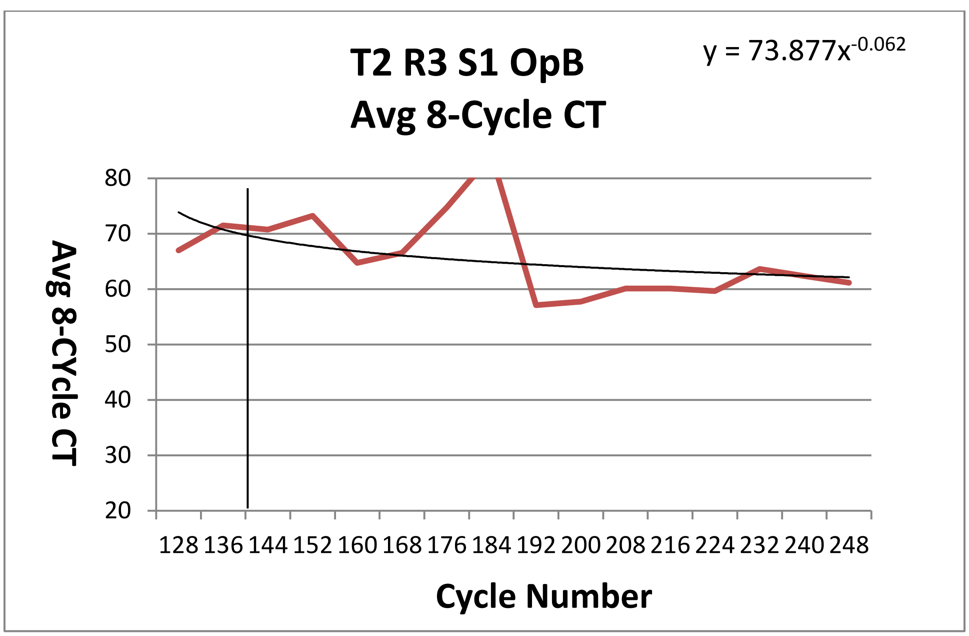


Team 1, Operator B, Station 2 Learning Curve w/ line at cycle 16 and power equation showing LCC

Team 2-Station 1-R3

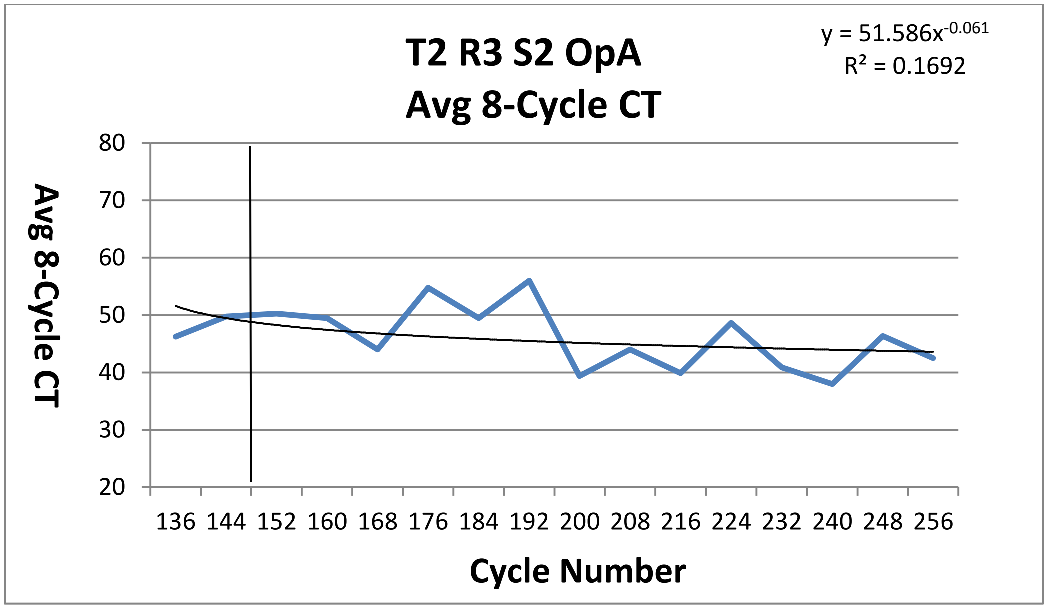


Team 2, Operator A, Station 1 Learning Curve w/ line at cycle 16 and power equation showing LCC

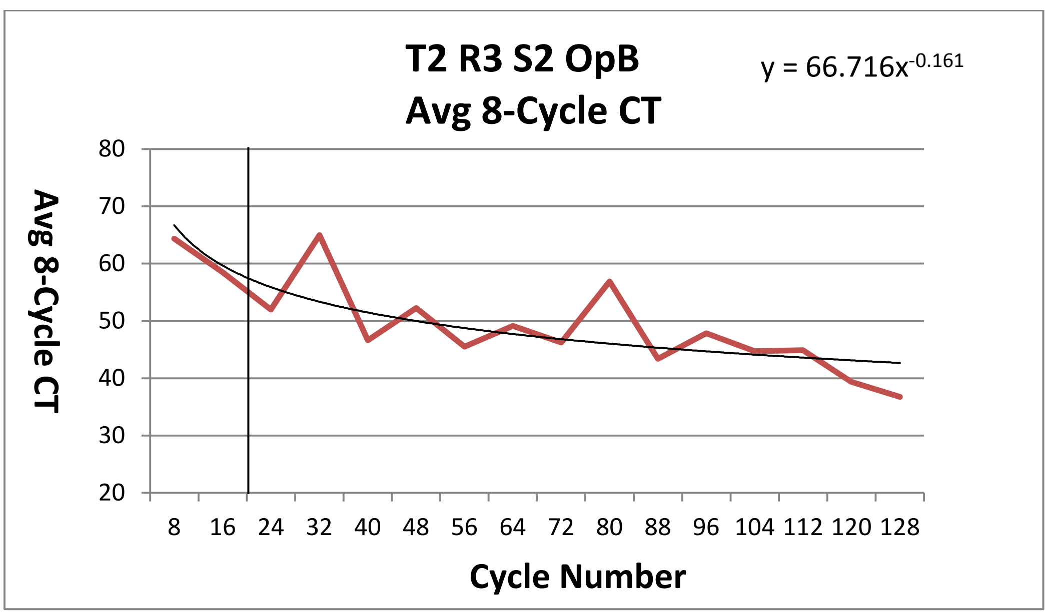


Team 2, Operator B, Station 1 Learning Curve w/ line at cycle 16 and power equation showing LCC

Team 2-Station 2-R3

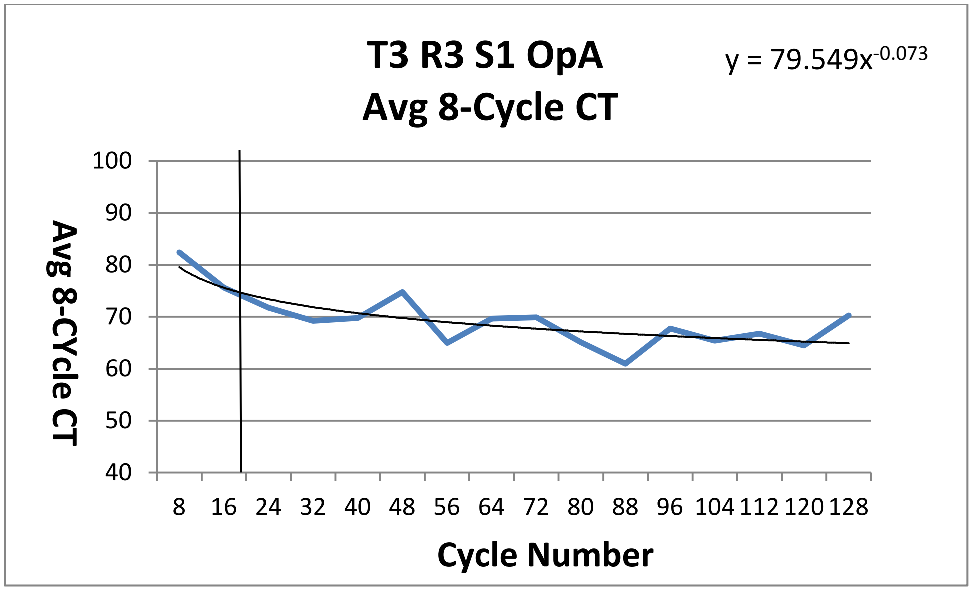


Team 2, Operator A, Station 2 Learning Curve w/ line at cycle 16 and power equation showing LCC

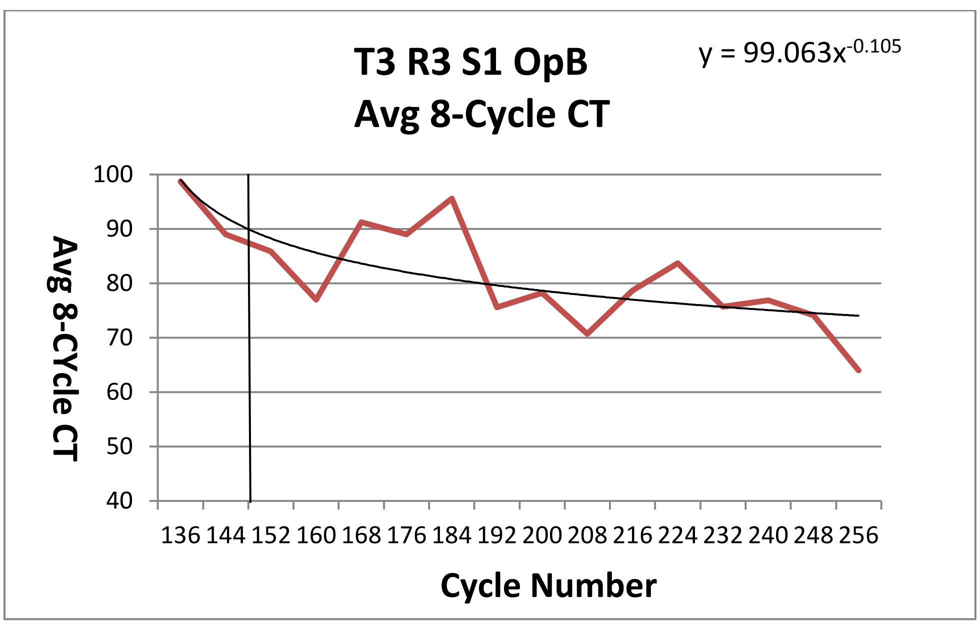


Team 2, Operator B, Station 2 Learning Curve w/ line at cycle 16 and power equation showing LCC

Team 3-Station 1-R3

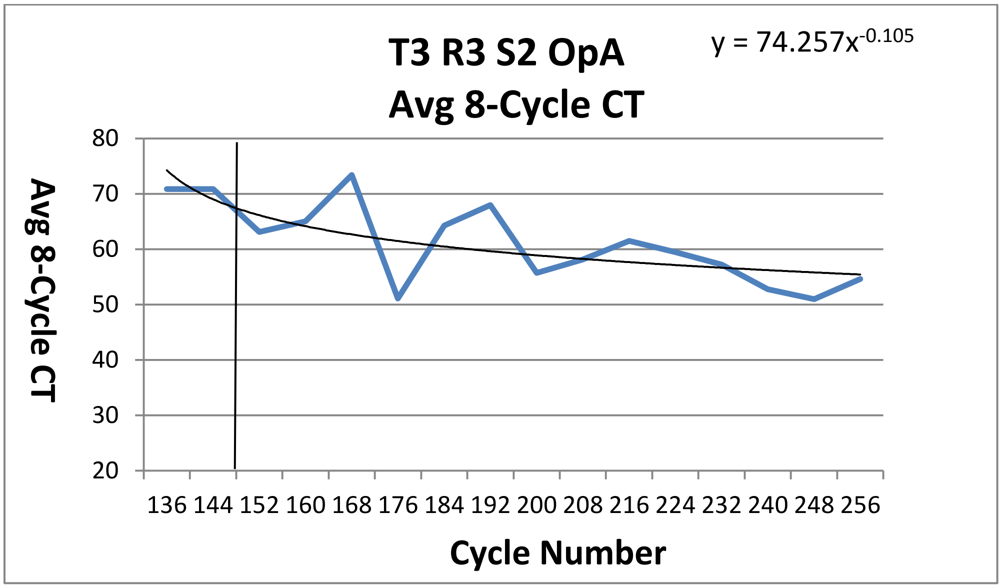


Team 3, Operator A, Station 1 Learning Curve w/ line at cycle 16 and power equation showing LCC

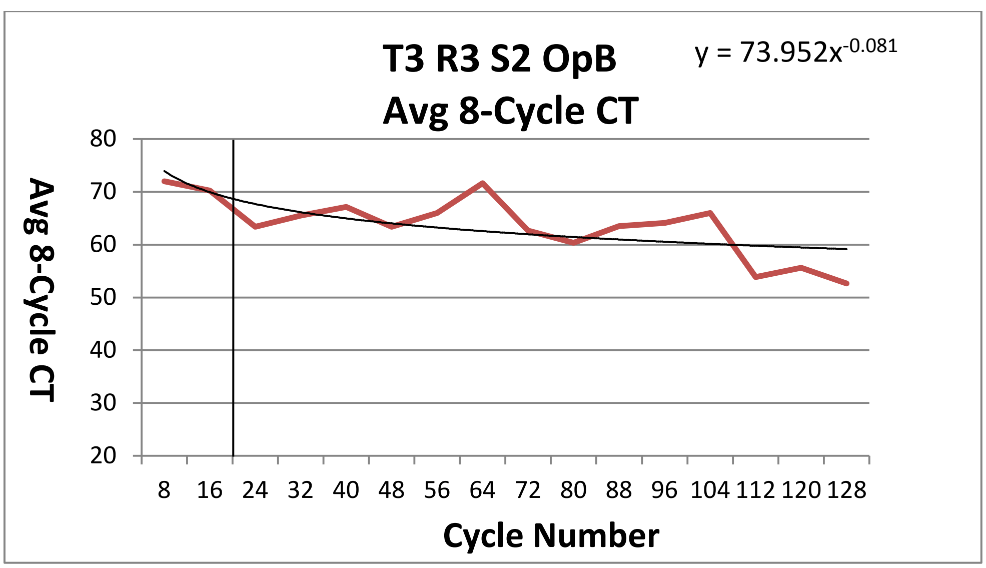


Team 3, Operator B, Station 1 Learning Curve w/ line at cycle 16 and power equation showing LCC

Team 3-Station 2-R3

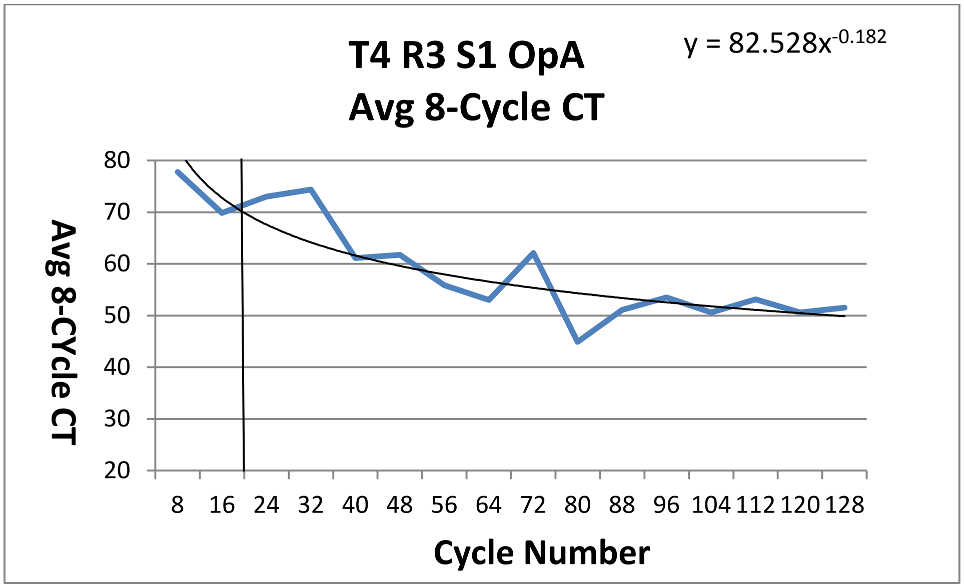


Team 3, Operator A, Station 2 Learning Curve w/ line at cycle 16 and power equation showing LCC

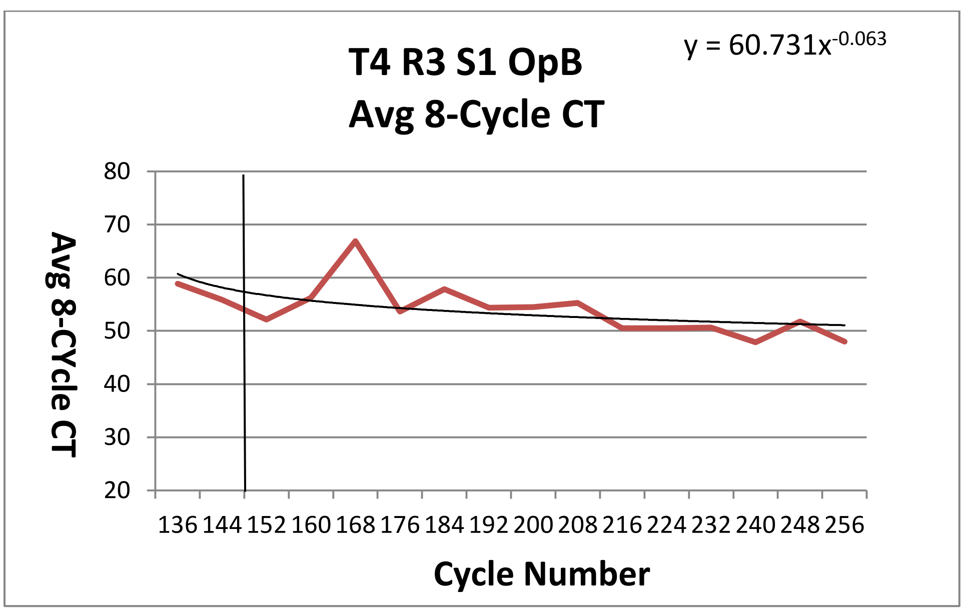


Team 3, Operator B, Station 2 Learning Curve w/ line at cycle 16 and power equation showing LCC

Team 4-Station 1-R3

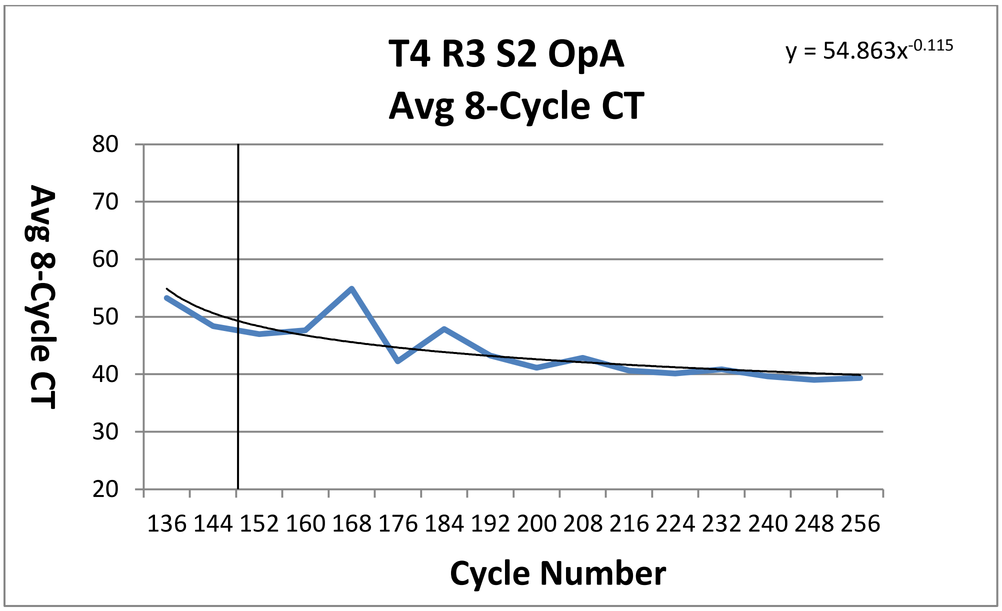


Team 4, Operator A, Station 1 Learning Curve w/ line at cycle 16 and power equation showing LCC

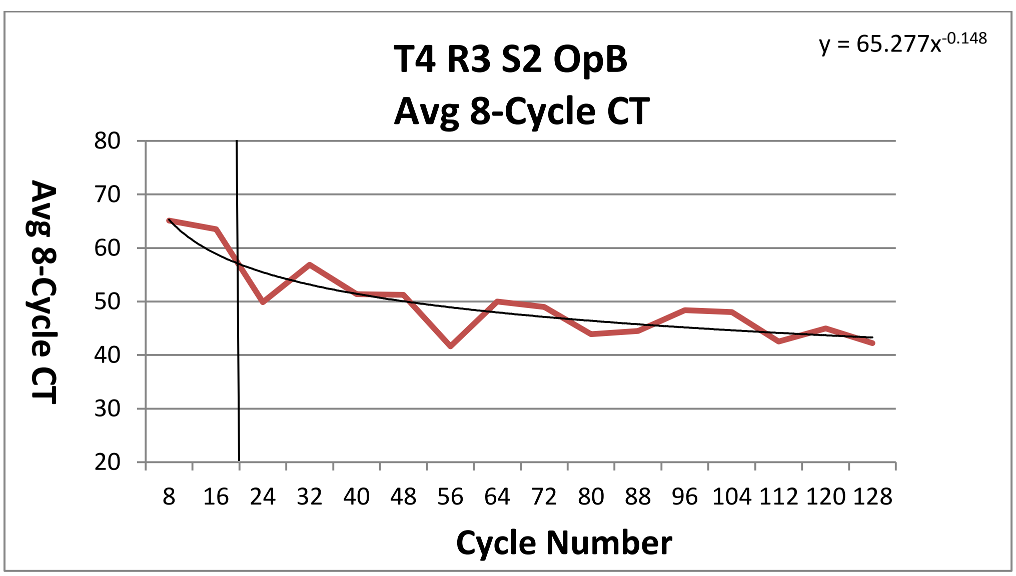


Team 4, Operator B, Station 1 Learning Curve w/ line at cycle 16 and power equation showing LCC

Team 4-Station 2-R3



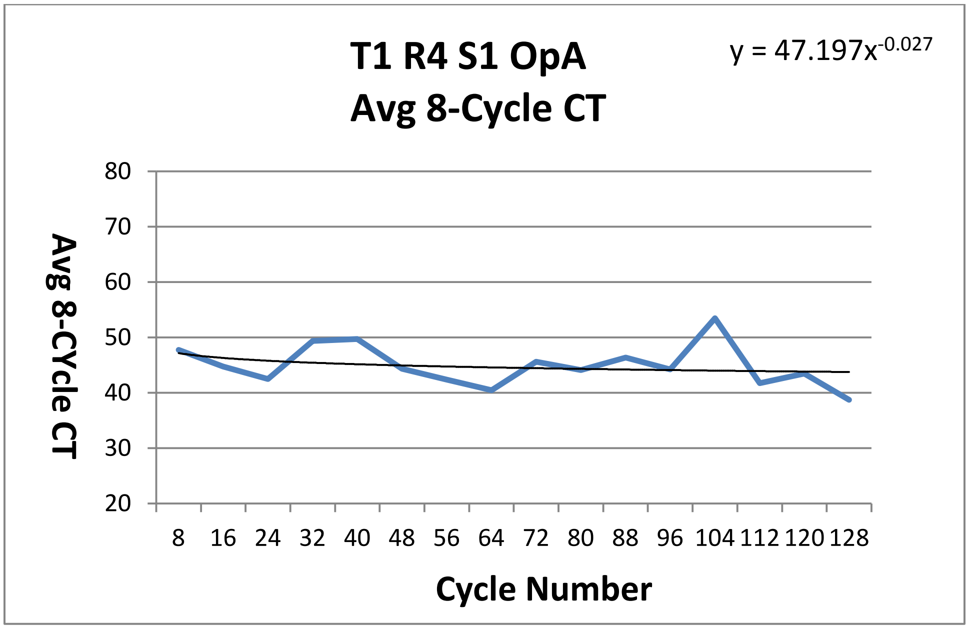
Team 4, Operator A, Station 2 Learning Curve w/ line at cycle 16 and power equation showing LCC

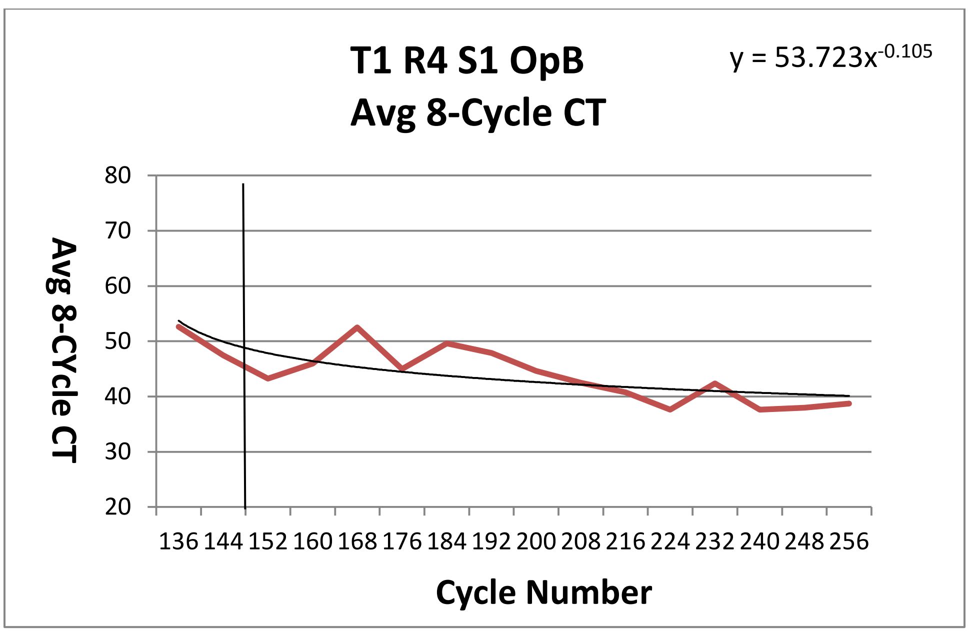


Team 4, Operator B, Station 2 Learning Curve w/ line at cycle 16 and power equation showing LCC

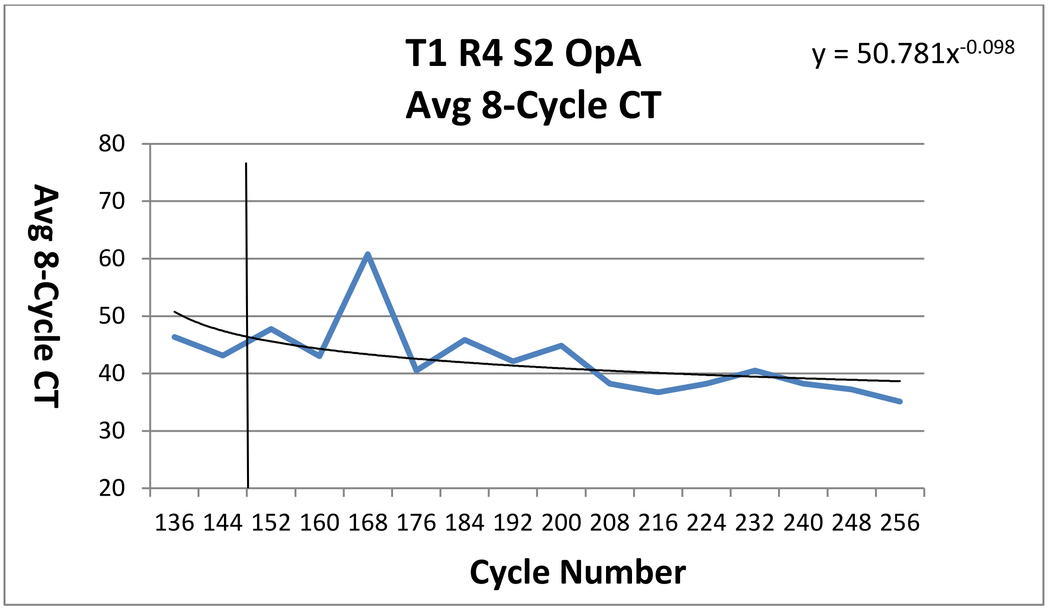
Appendix G: 128-Cycle Learning Curves with 16-Cycle Marker

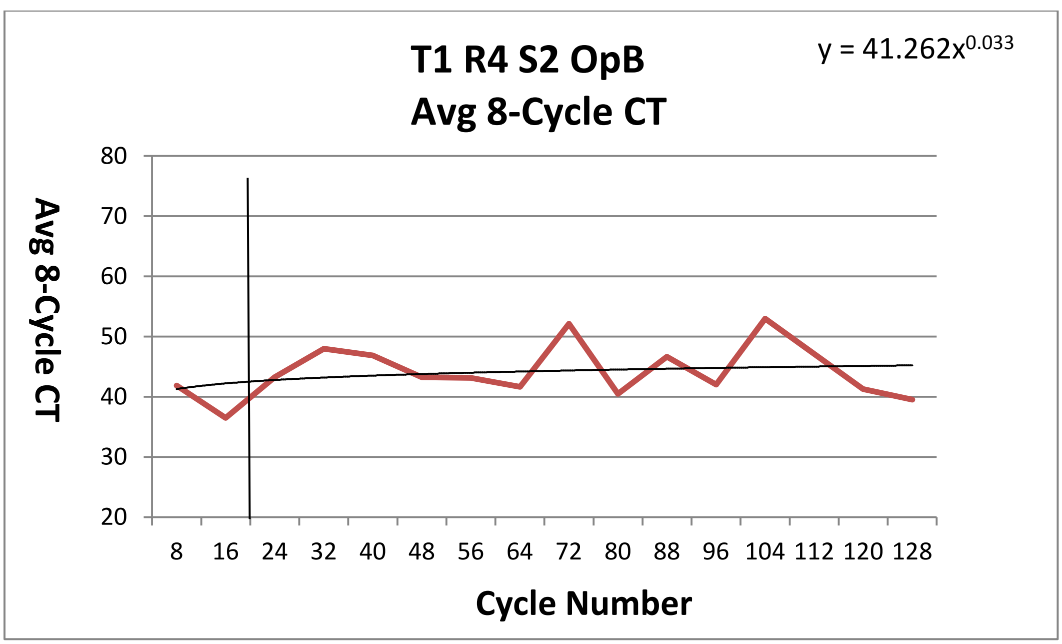
Team 1-Station 1-R4



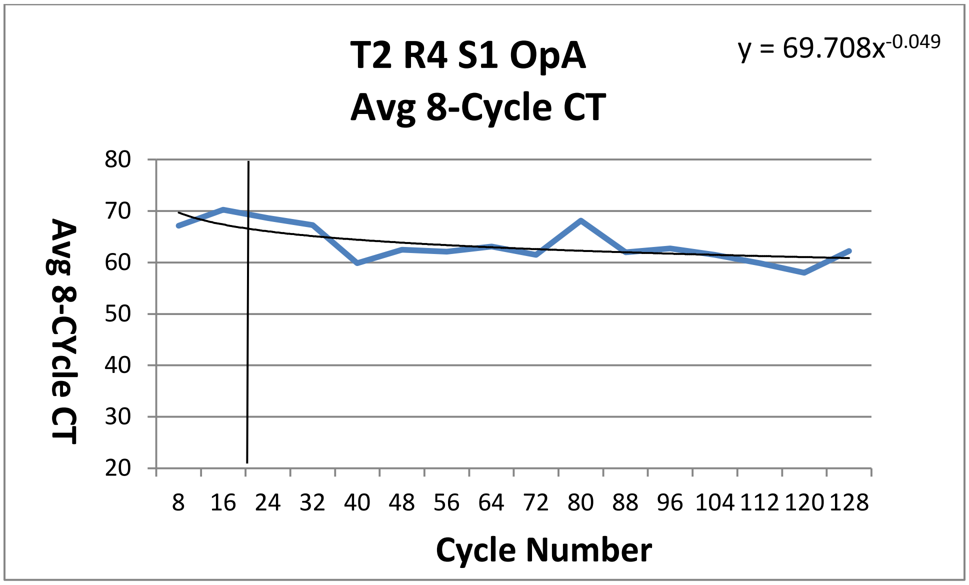


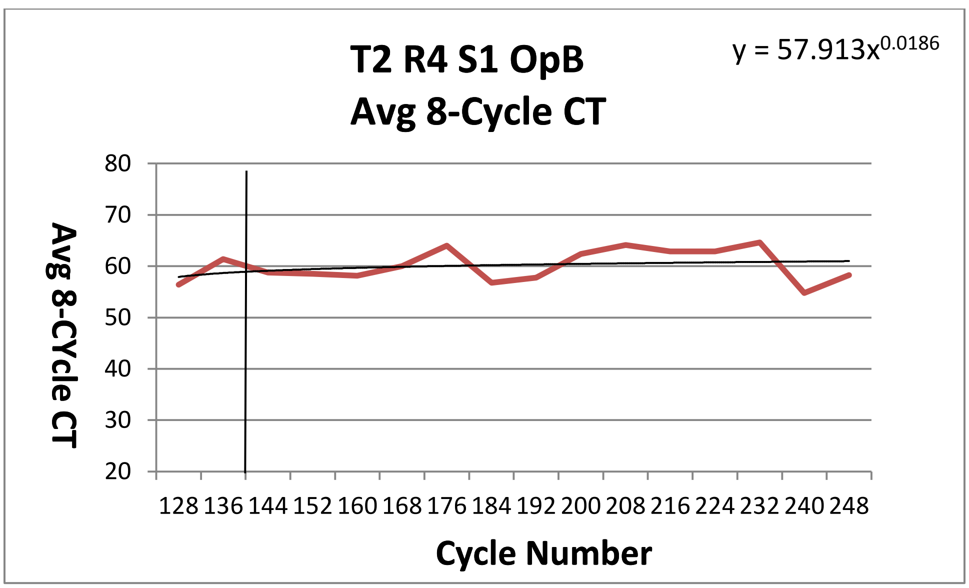
Team 1-Station 2-R4



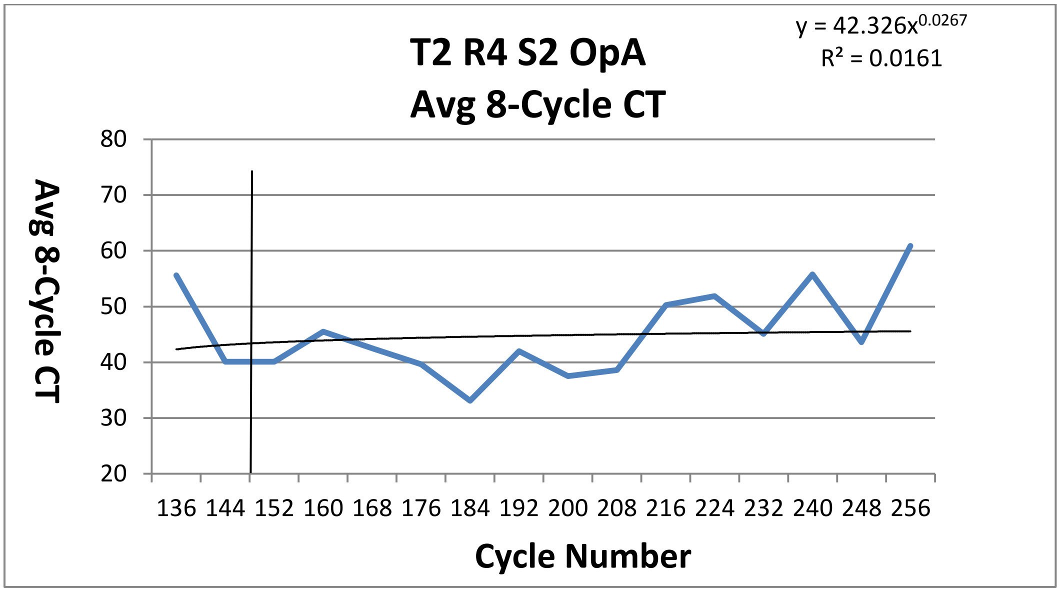


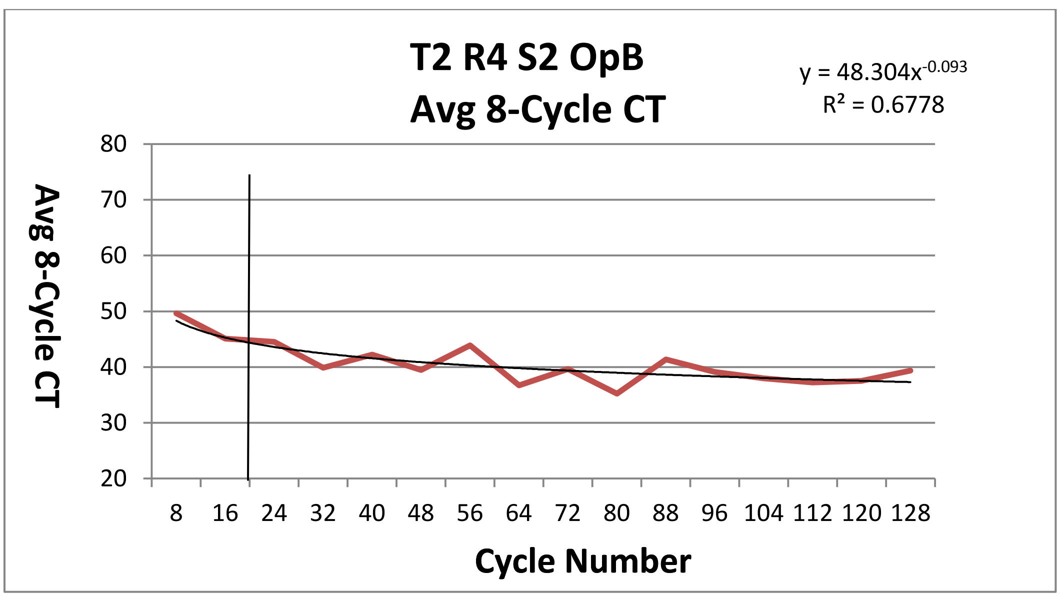
Team 2-Station 1-R4



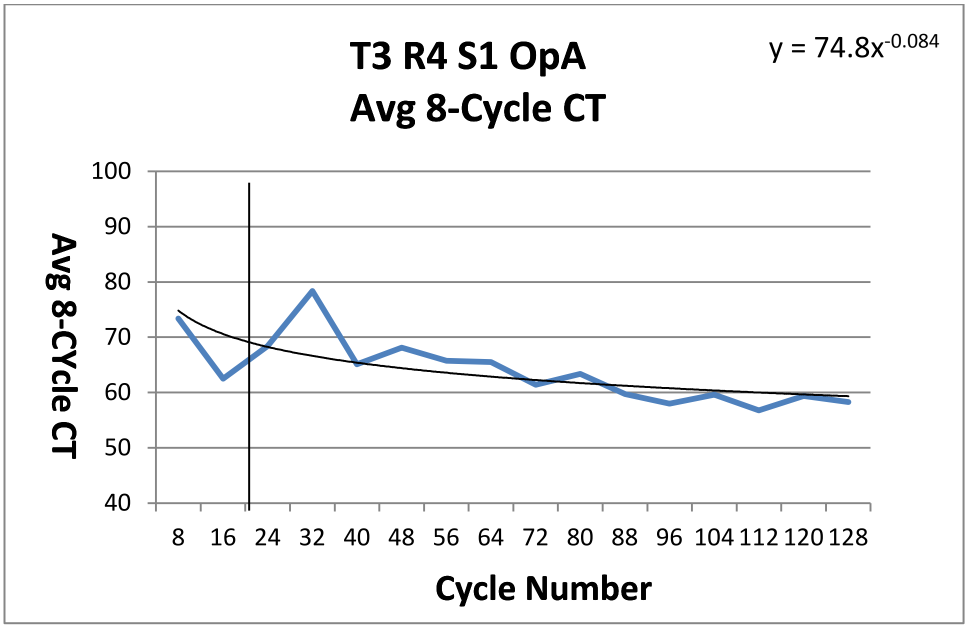


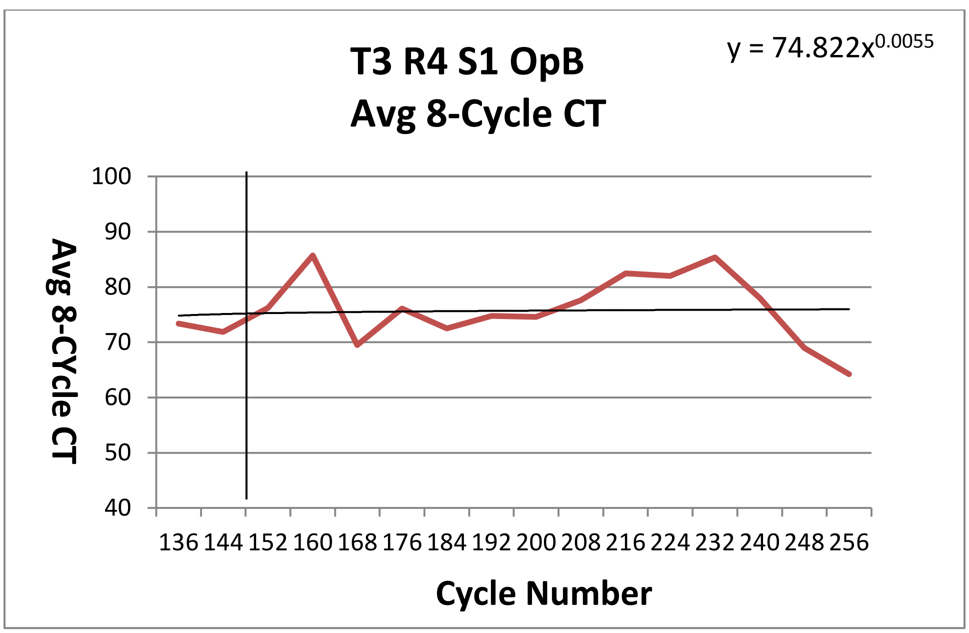
Team 2-Station 2-R4



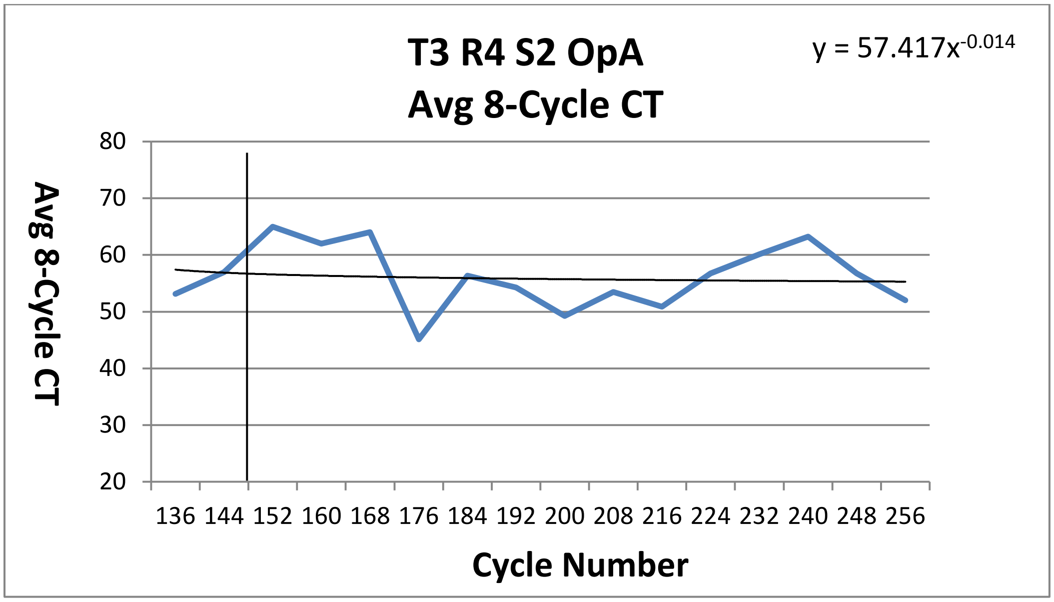


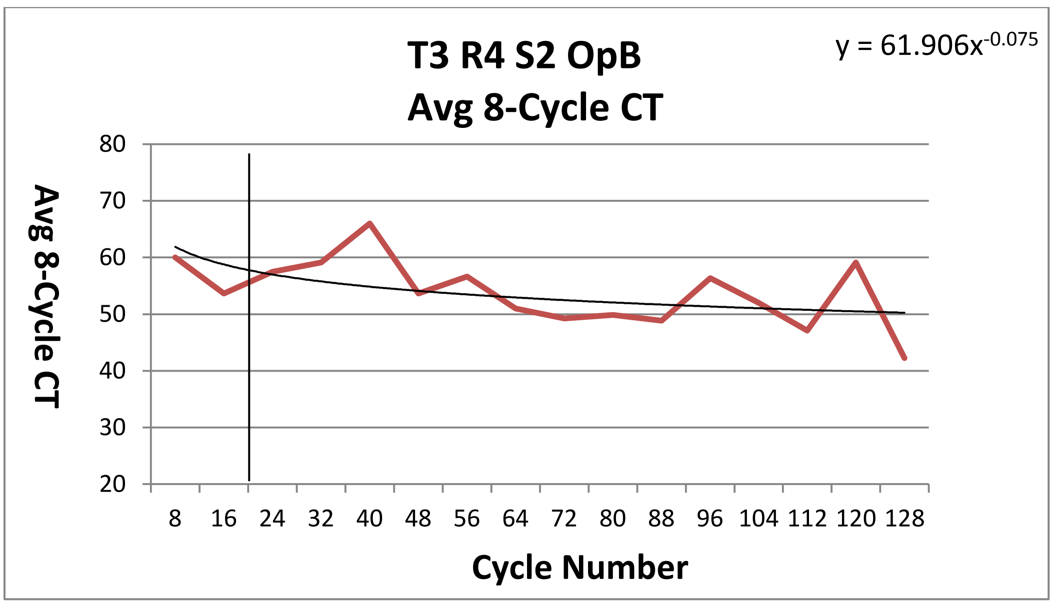
Team 3-Station 1-R4



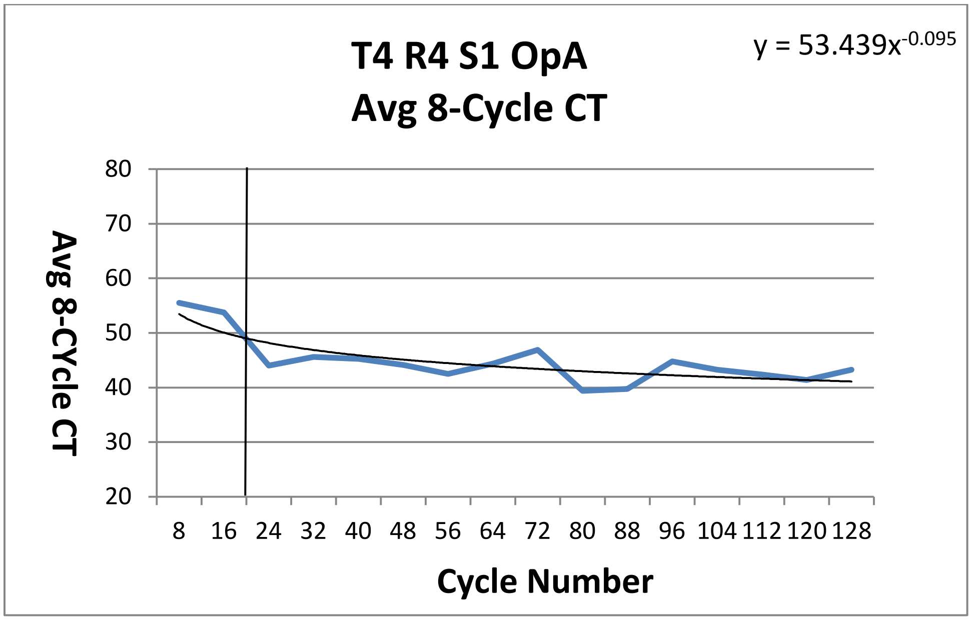


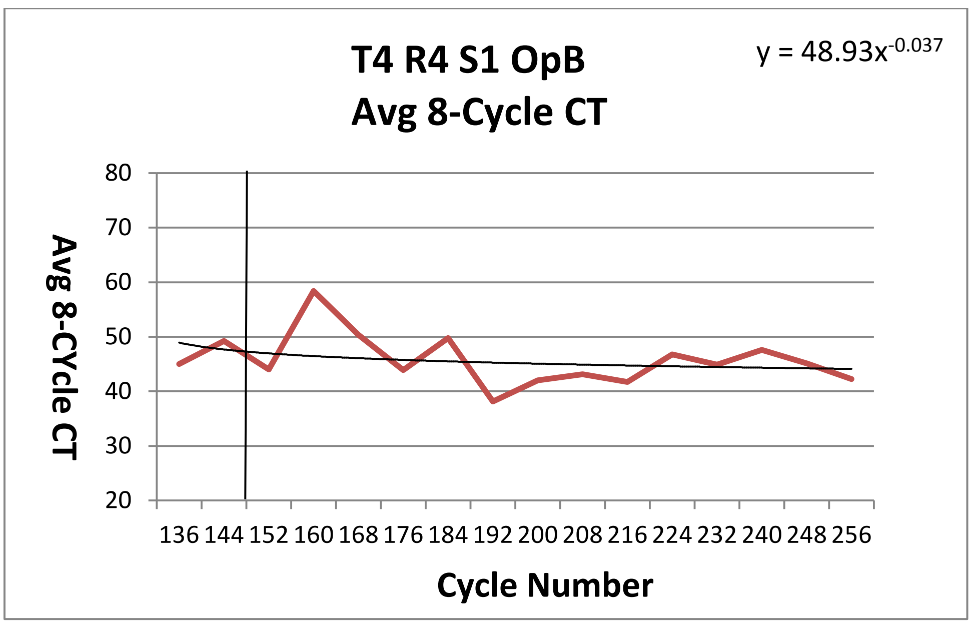
Team 3-Station 2-R4



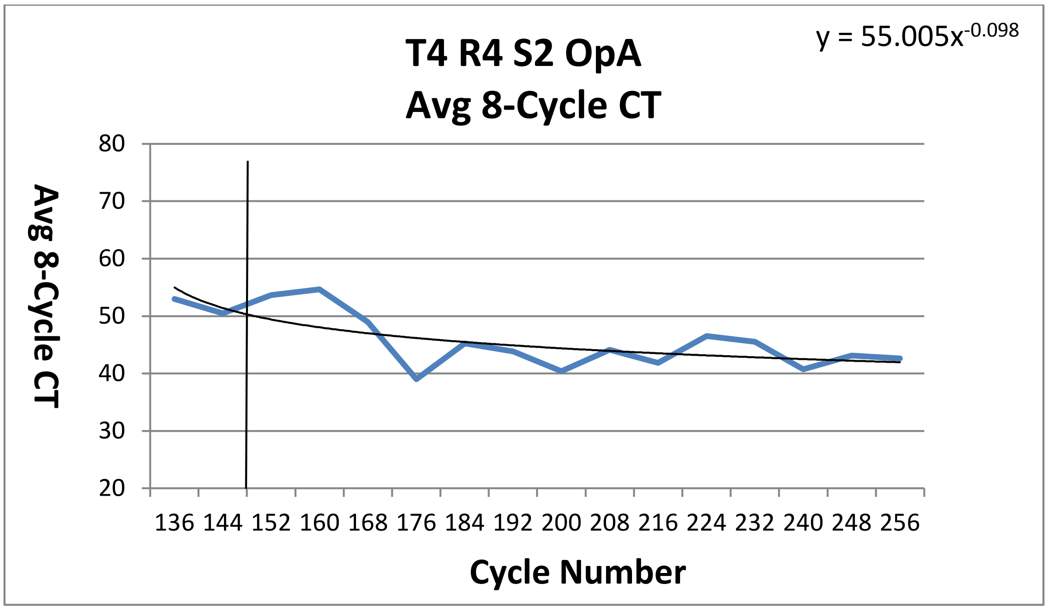


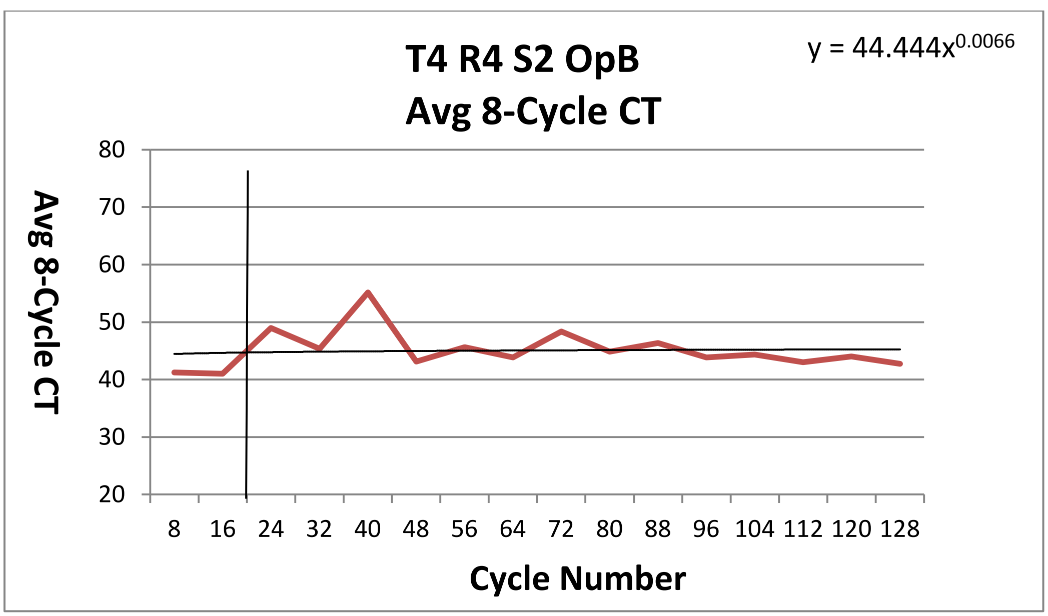
Team 4-Station 1-R4





Team 4-Station 2-R4





Appendix H: Statistical Results for 128 versus 112-Cycle LCC Data

Station-Specific R3

t-Test: Paired Two Sample for Means

R3 Station 1	*Station 1-128 cycles*	*Station 1-112 cycles*
Mean	-0.088375	-0.083625
Variance	0.00198	0.00170
Observations	8	8
Pearson Correlation	0.827	
Hypothesized Mean Difference	0	
df	7	
t Stat	-0.529	
P(T<=t) two-tail	0.613	
t Critical two-tail	2.365	

R3 Station 1, using combined treated and untreated team LCC results

t-Test: Paired Two Sample for Means

R3 Station 2	*128 Cycles*	*112 Cycles*
Mean	-0.11475	-0.093375
Variance	0.00122	0.00116
Observations	8	8
Pearson Correlation	0.637	
Hypothesized Mean Difference	0	
df	7	
t Stat	-2.055	
P(T<=t) two-tail	0.079	
t Critical two-tail	2.365	

R3 Station 2, using combined treated and untreated team LCC results

Appendix I: Statistical Results for 128 versus 112-Cycle LCC Data

Operator-Specific R3

t-Test: Paired Two Sample for Means

R3 Operator A	*128 Cycles*	*112 Cycles*
Mean	-0.10088	-0.08538
Variance	0.001656	0.00171
Observations	8	8
Pearson Correlation	0.893402	
Hypothesized Mean Difference	0	
df	7	
t Stat	-2.31336	
P(T<=t) two-tail	0.053919	
t Critical two-tail	2.364624	

R3 Operator A, using combined treated and untreated team LCC Results

t-Test: Paired Two Sample for Means

R3 Operator B	*128 Cycles*	*112 Cycles*
Mean	-0.10475	-0.09163
Variance	0.001769	0.00118
Observations	8	8
Pearson Correlation	0.623613	
Hypothesized Mean Difference	0	
df	7	
t Stat	-1.09614	
P(T<=t) two-tail	0.30929	
t Critical two-tail	2.364624	

R3 Operator B, using combined treated and untreated team LCC Results

Appendix J: Statistical Results for Combined 128 versus 112-Cycle LCC Data

Station-Specific R4

t-Test: Paired Two Sample for Means

R4 Station 1	*128 Cycles*	*112 Cycles*
Mean	-0.05125	-0.038625
Variance	0.00157	0.00128
Observations	8	8
Pearson Correlation	0.699	
Hypothesized Mean Difference	0	
df	7	
t Stat	-1.211	
P(T<=t) two-tail	0.265	
t Critical two-tail	2.365	

R4 Station 1, using combined treated and untreated team LCC results

t-Test: Paired Two Sample for Means

R4 Station 2	*128 Cycles*	*112 Cycles*
Mean	-0.038875	-0.044875
Variance	0.00335	0.00454
Observations	8	8
Pearson Correlation	0.608	
Hypothesized Mean Difference	0	
df	7	
t Stat	0.302	
P(T<=t) two-tail	0.771	
t Critical two-tail	2.365	

R4 Station 2, using combined treated and untreated team LCC results

Appendix K: Statistical Results for 128 versus 112-Cycle LCC Data

Operator-Specific R4

t-Test: Paired Two Sample for Means

R4 Operator A	*128 Cycles*	*112 Cycles*
Mean	-0.05475	-0.03725
Variance	0.002195	0.004265
Observations	8	8
Pearson Correlation	0.776377	
Hypothesized Mean Difference	0	
df	7	
t Stat	-1.19737	
P(T<=t) two-tail	0.27013	
t Critical two-tail	2.364624	

R4 Operator A, using combined treated and untreated team LCC Results

t-Test: Paired Two Sample for Means

R4 Operator B	*128 Cycles*	*112 Cycles*
Mean	-0.10475	-0.09163
Variance	0.001769	0.00118
Observations	8	8
Pearson Correlation	0.623613	
Hypothesized Mean Difference	0	
df	7	
t Stat	-1.09614	
P(T<=t) two-tail	0.30929	
t Critical two-tail	2.364624	

R4 Operator B, using combined treated and untreated team LCC Results

Appendix L: R3 Individual Station-Specific Two-Sided t-Test Results

t-Test: Two-Sample Assuming Equal Variances

R3-Station 1	*Untreated*	*Treated*
Mean	-0.05575	-0.1115
Variance	0.000523	0.001363
Observations	4	4
Pooled Variance	0.000943	
Hypothesized Mean Difference	0	
df	6	
t Stat	2.567519	
P(T<=t) two-tail	0.042477	
t Critical two-tail	2.446912	

R3 Station 1, using individual Station-specific LCC results

t-Test: Two-Sample Assuming Equal Variances

R3-Station 2	*Untreated*	*Treated*
Mean	-0.08375	-0.103
Variance	0.000764	0.001698
Observations	4	4
Pooled Variance	0.001231	
Hypothesized Mean Difference	0	
df	6	
t Stat	0.77588	
P(T<=t) two-tail	0.467291	
t Critical two-tail	2.446912	

R3 Station 2, using individual Station-specific LCC results

t-Test: Two-Sample Assuming Equal Variances

R4-Station 1	*Untreated*	*Treated*
Mean	-0.03325	-0.044
Variance	0.002113	0.000806
Observations	4	4
Pooled Variance	0.001459	
Hypothesized Mean Difference	0	
df	6	
t Stat	0.397949	
P(T<=t) two-tail	0.704441	
t Critical two-tail	2.446912	

R4 Station 1, using individual Station-specific LCC results

t-Test: Two-Sample Assuming Equal Variances

R4-Station 2	*Untreated*	*Treated*
Mean	-0.02175	-0.068
Variance	0.006749	0.002411
Observations	4	4
Pooled Variance	0.00458	
Hypothesized Mean Difference	0	
df	6	
t Stat	0.966469	
P(T<=t) two-tail	0.371134	
t Critical two-tail	2.446912	

R4 Station 2, using individual Station-specific LCC results

Appendix M: R3 Combined Individual Station-Specific Two-Sided t-Test Results

t-Test: Two-Sample Assuming Equal Variances

R3-Station1+Station 2		*Treated*
Mean	-0.06975	-0.10725
Variance	0.000776	0.001333
Observations	8	8
Pooled Variance	0.001054	
Hypothesized Mean Difference	0	
df	14	
t Stat	2.310076	
P(T<=t) two-tail	0.036643	
t Critical two-tail	2.144787	

R3 Stations 1 and 2, using combined LCC results (Same as combined operator results)

t-Test: Two-Sample Assuming Equal Variances

R4-Station1+Station 2		*Treated*
Mean	-0.0275	-0.056
Variance	0.003836	0.001543
Observations	8	8
Pooled Variance	0.00269	
Hypothesized Mean Difference	0	
df	14	
t Stat	1.09909	
P(T<=t) two-tail	0.290271	
t Critical two-tail	2.144787	

R4 Station 1 and 2, using combined LCC results (same as combined operator results)

Appendix N: R4 Individual Operator-Specific Two-Sided t-Test Results

t-Test: Two-Sample Assuming Equal Variances

R3-Operator A	*Untreated*	*Treated*
Mean	-0.05725	-0.1135
Variance	0.000606	0.001274
Observations	4	4
Pooled Variance	0.00094	
Hypothesized Mean Difference	0	
df	6	
t Stat	2.594677	
P(T<=t) two-tail	0.040954	
t Critical two-tail	2.446912	

R3 Operator A, using individual Station-specific LCC results

t-Test: Two-Sample Assuming Equal Variances

R3-Operator B	*Untreated*	*Treated*
Mean	-0.08225	-0.101
Variance	0.000787	0.001731
Observations	4	4
Pooled Variance	0.001259	
Hypothesized Mean Difference	0	
df	6	
t Stat	0.747277	
P(T<=t) two-tail	0.483142	
t Critical two-tail	2.446912	

R3 Operator, using individual Station-specific LCC results

t-Test: Two-Sample Assuming Equal Variances

R4-Operator A	*Untreated*	*Treated*
Mean	-0.02025	-0.05425
Variance	0.006915	0.002265
Observations	4	4
Pooled Variance	0.00459	
Hypothesized Mean Difference	0	
df	6	
t Stat	0.709727	
P(T<=t) two-tail	0.504507	
t Critical two-tail	2.446912	

R4 Operator A, using individual Station-specific LCC results

t-Test: Two-Sample Assuming Equal Variances

R4-Operator B	*Untreated*	*Treated*
Mean	-0.03475	-0.05775
Variance	0.001895	0.001328
Observations	4	4
Pooled Variance	0.001612	
Hypothesized Mean Difference	0	
df	6	
t Stat	0.810245	
P(T<=t) two-tail	0.448734	
t Critical two-tail	2.446912	

R4 Operator B, using individual Station-specific LCC results

Appendix O: R4 Combined Individual Operator-Specific Two-Sided t-Test Results

t-Test: Two-Sample Assuming Equal Variances

R3-Operator A+Operator B	*Untreated*	*Treated*
Mean	-0.06975	-0.10725
Variance	0.000776	0.001333
Observations	8	8
Pooled Variance	0.001054	
Hypothesized Mean Difference	0	
df	14	
t Stat	2.310076	
P(T<=t) two-tail	0.036643	
t Critical two-tail	2.144787	

R3 Operators A and B, using combined LCC results (Same as combined Station results)

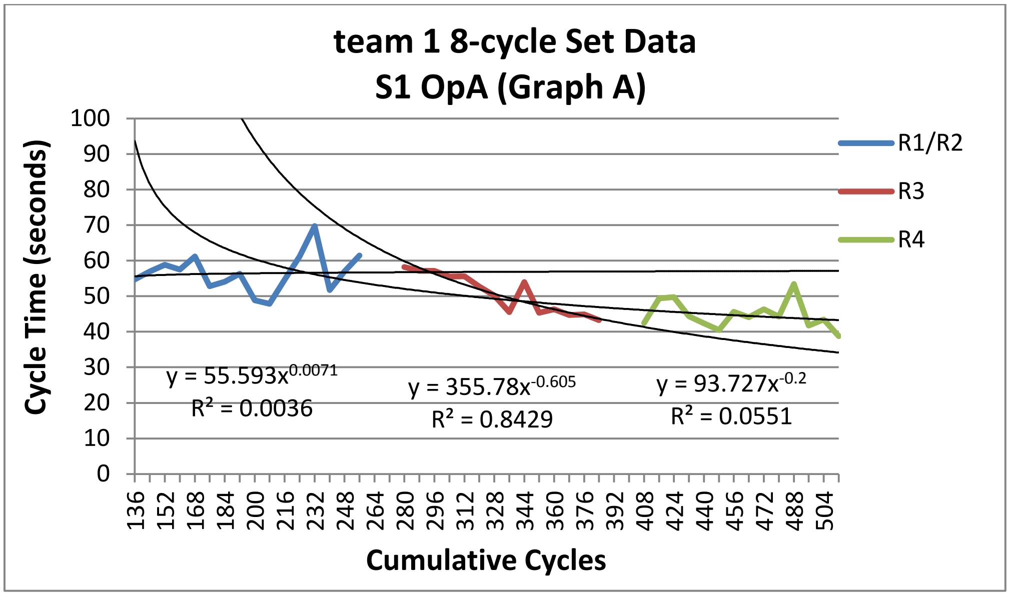
t-Test: Two-Sample Assuming Equal Variances

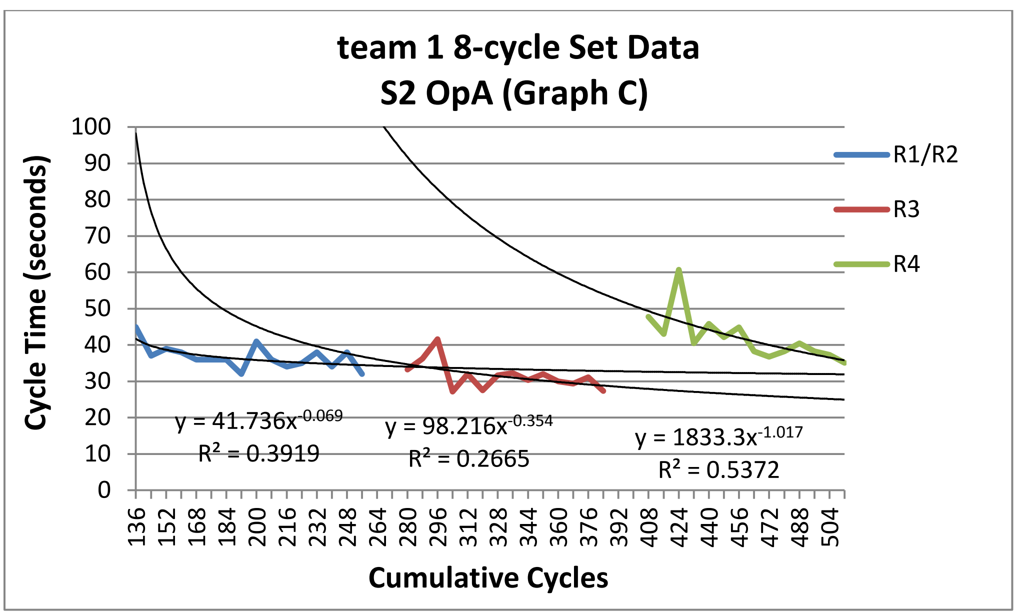
R4-Operator A+Operator B	*Untreated*	*Treated*
Mean	-0.0275	-0.056
Variance	0.003836	0.001543
Observations	8	8
Pooled Variance	0.00269	
Hypothesized Mean Difference	0	
df	14	
t Stat	1.09909	
P(T<=t) two-tail	0.290271	
t Critical two-tail	2.144787	

R4 Operators A and B, using combined LCC results (Same as combined Station results)

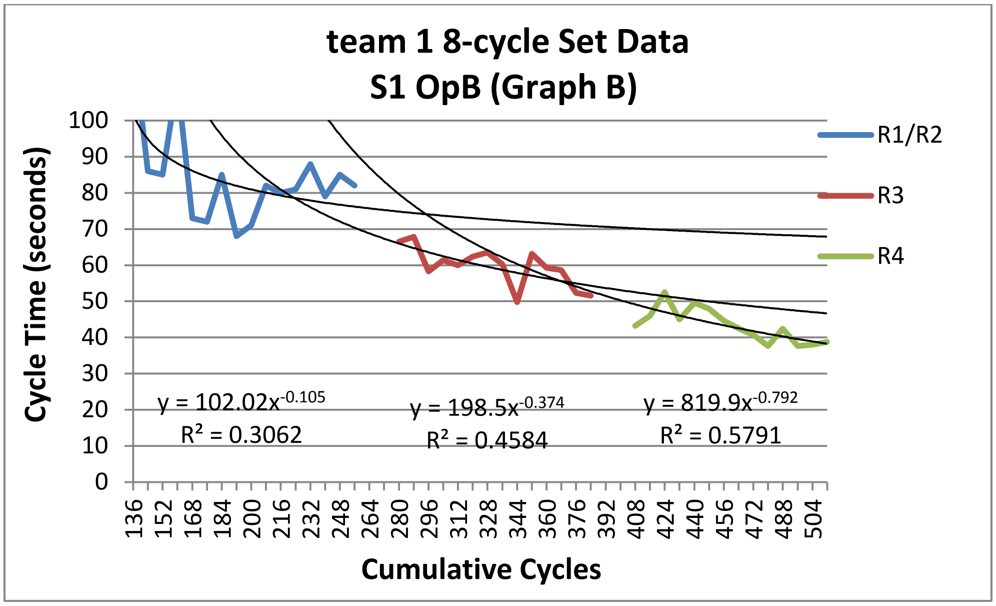
Appendix P: Contextual Learning Curves for R1/R2, R3 and R4

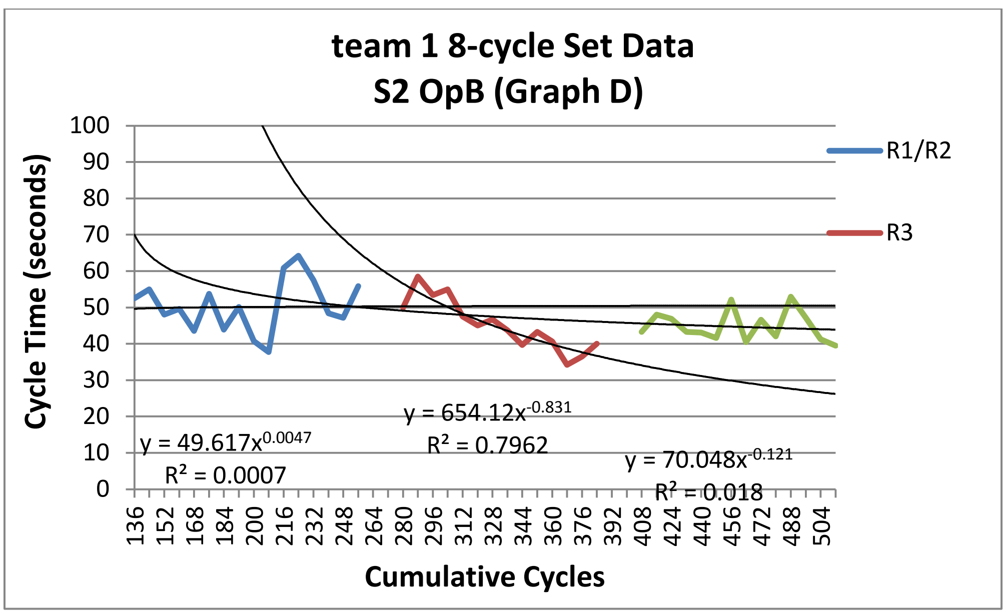
Team 1-Operator A, Station 1 and 2



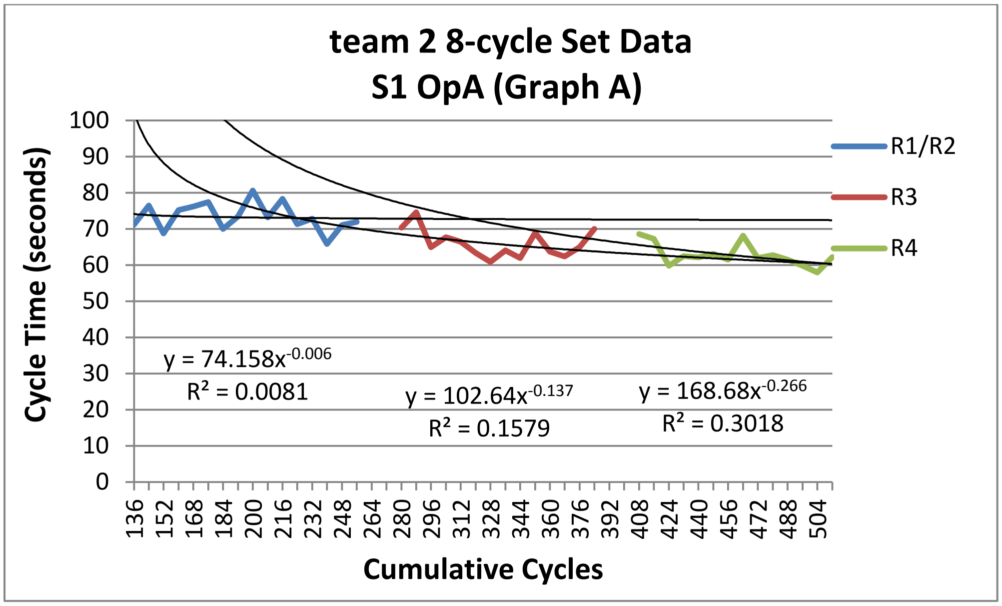


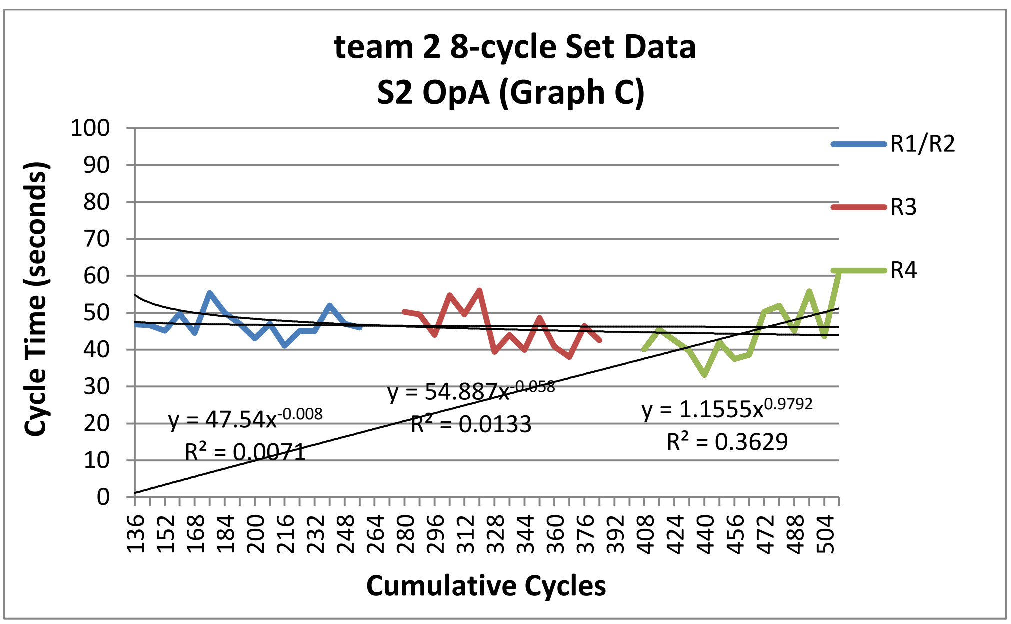
Team 1-Operator B, Station 1 and 2



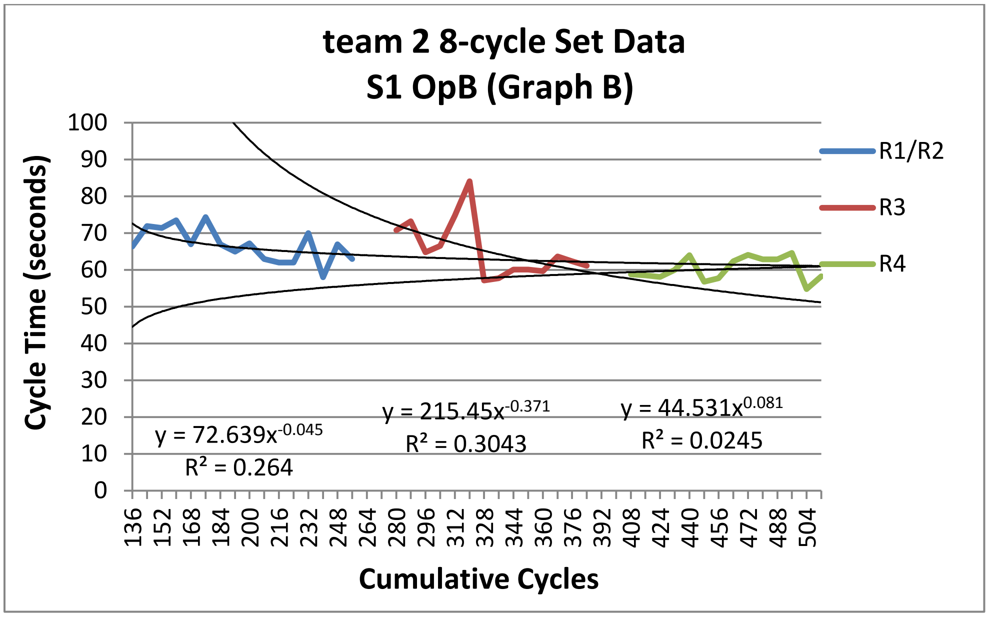


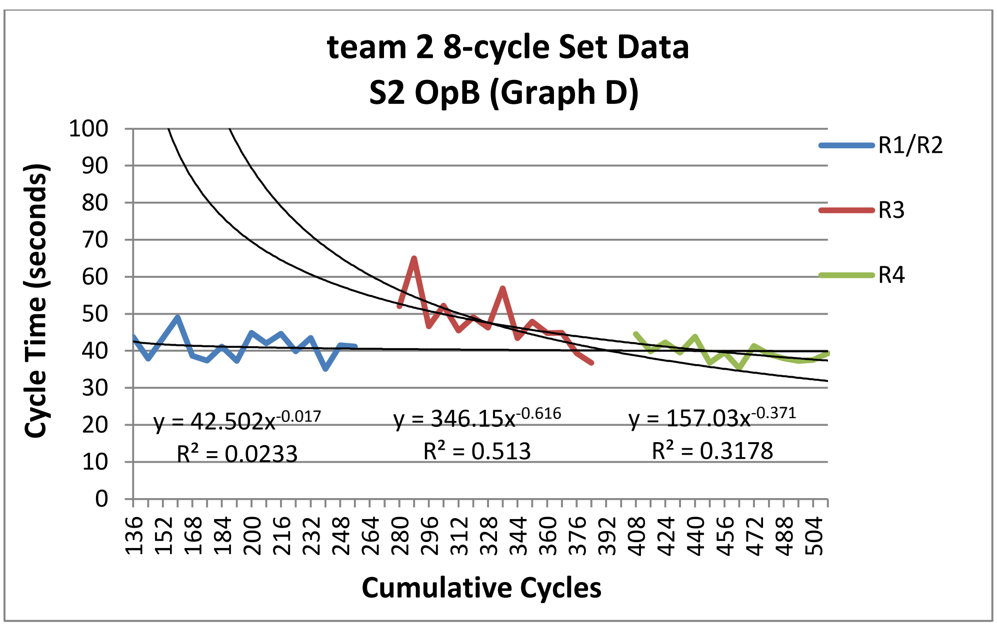
Team 2-Operator A, Station 1 and 2



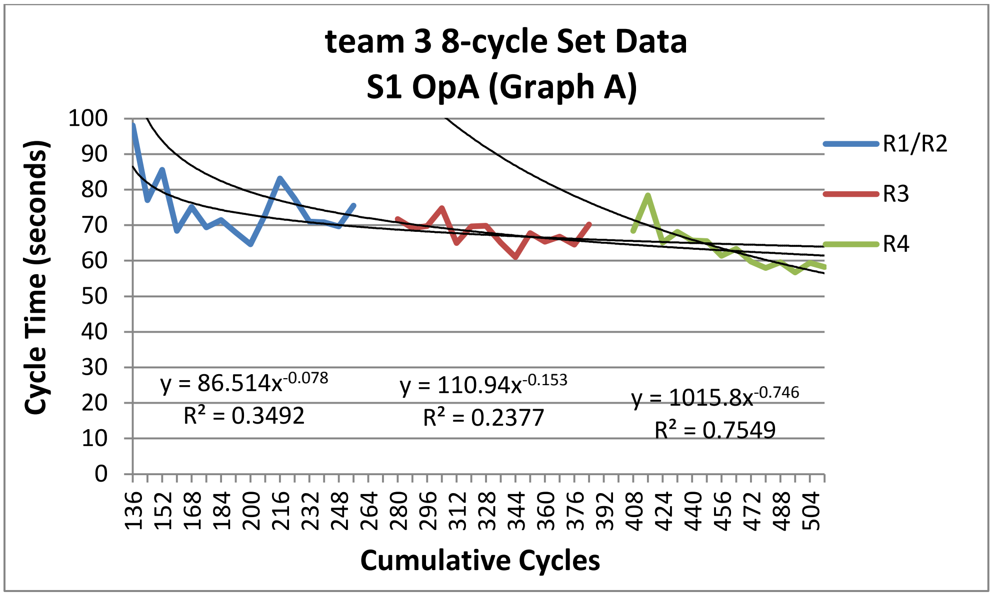


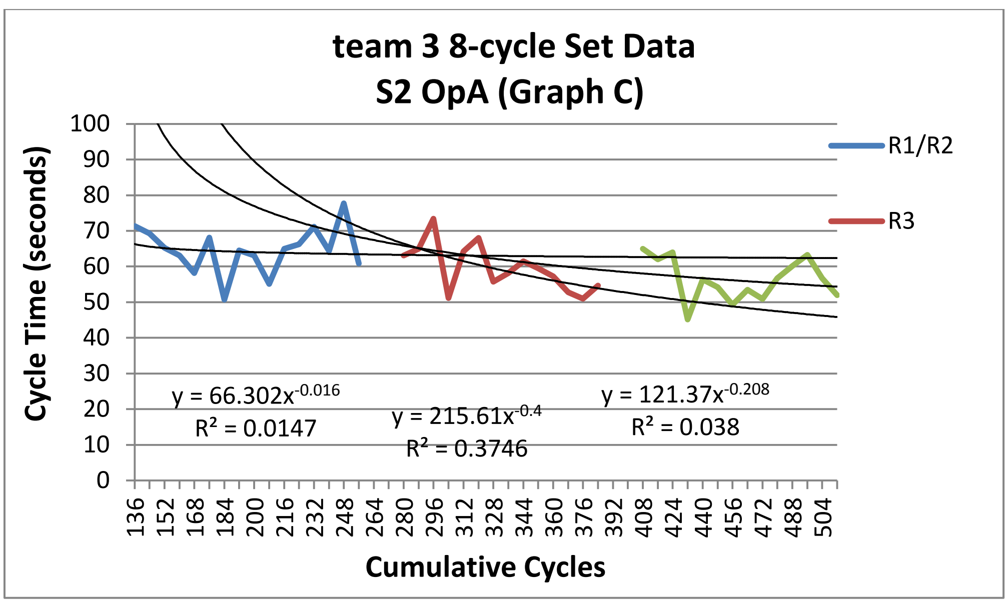
Team 2-Operator B, Station 1 and 2



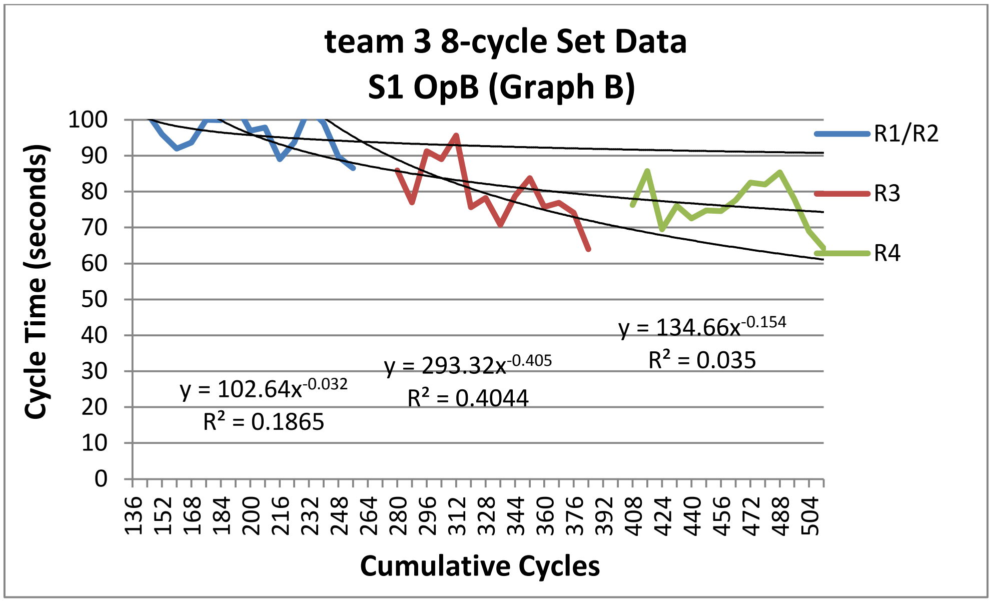


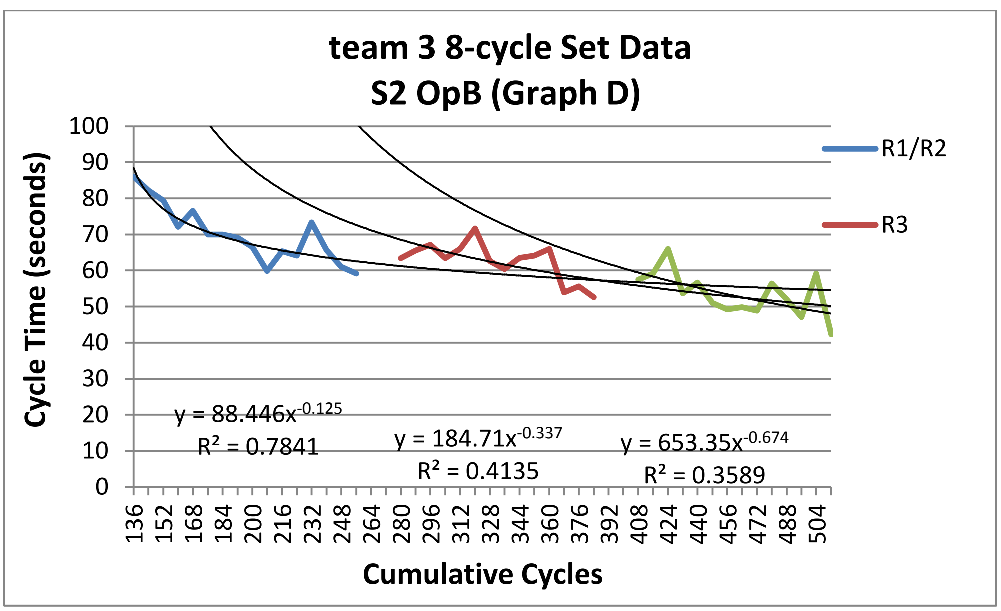
Team 3-Operator A, Station 1 and 2



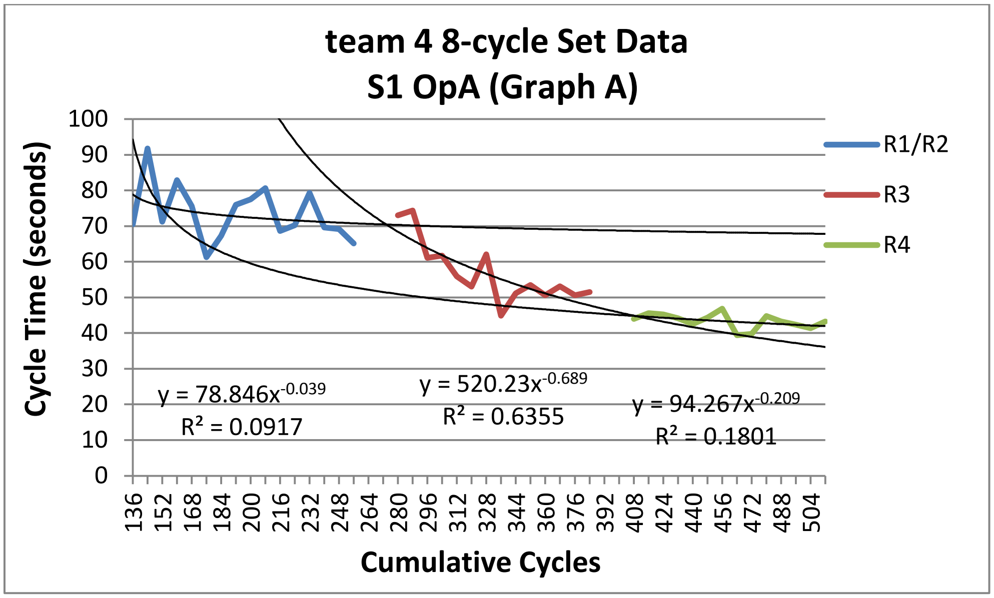


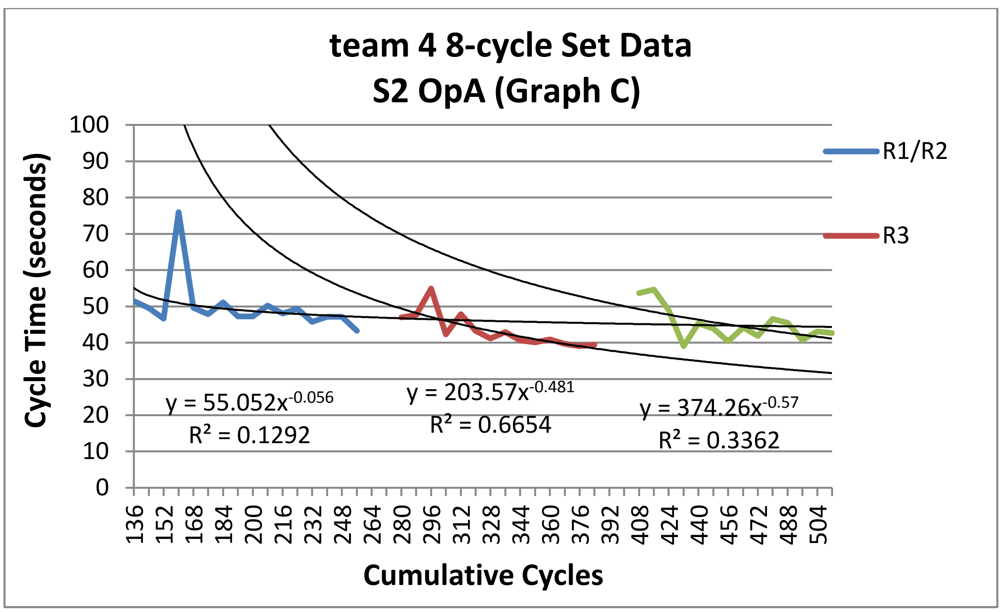
Team 3-Operator B, Station 1 and 2



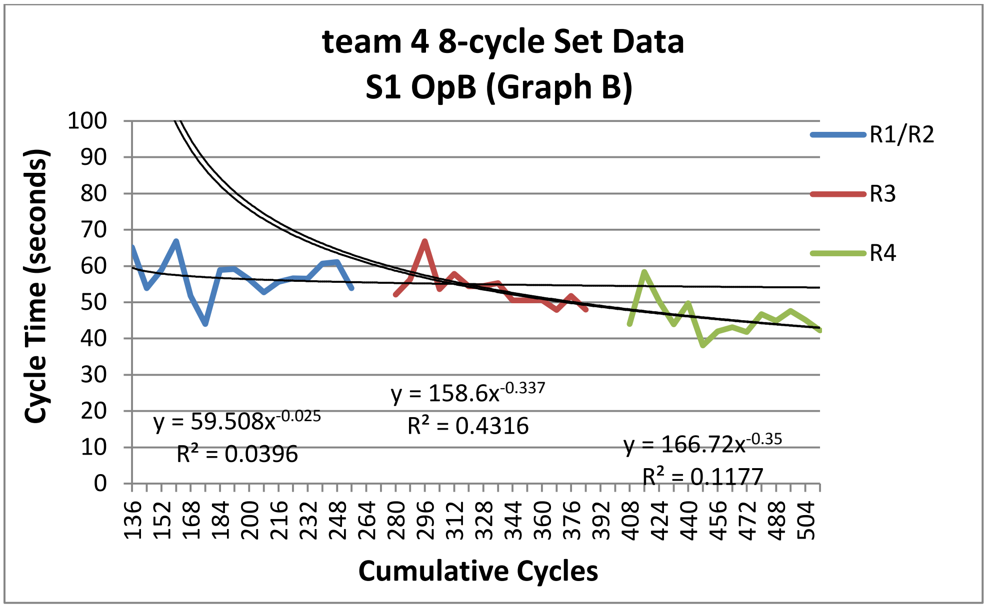


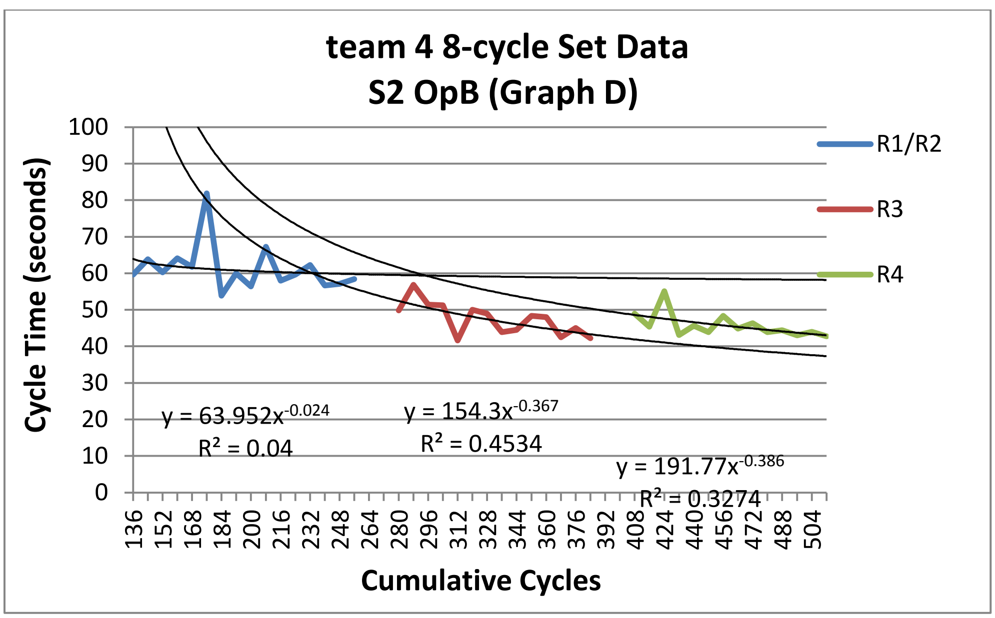
Team 4-Operator A, Station 1 and 2





Team 4-Operator B, Station 1 and 2





Appendix Q: Two-Sided t-Test Results for Contextual R3 and R4 LCC Data

Station-Specific

t-Test: Two-Sample Assuming Equal Variances

R3 Station 1	*Treated*	*Untreated*
Mean	-0.50125	-0.2665
Variance	0.029728	0.019918
Observations	4	4
Pooled Variance	0.024823	
Hypothesized Mean Difference	0	
df	6	
t Stat	-2.10713	
P(T<=t) two-tail	0.079689	
t Critical two-tail	2.446912	

t-Test: Two-Sample Assuming Equal Variances

R3 Station 2	*Treated*	*Untreated*
Mean	-0.50825	-0.43825
Variance	0.049552	0.014924
Observations	4	4
Pooled Variance	0.032238	
Hypothesized Mean Difference	0	
df	6	
t Stat	-0.55135	
P(T<=t) two-tail	0.601305	
t Critical two-tail	2.446912	

t-Test: Two-Sample Assuming Equal Variances

R4 Station 1	*Treated*	*Untreated*
Mean	-0.38775	-0.31175
Variance	0.077348	0.089599
Observations	4	4
Pooled Variance	0.083474	
Hypothesized Mean Difference	0	
df	6	
t Stat	-0.37201	
P(T<=t) two-tail	0.722671	
t Critical two-tail	2.446912	

t-Test: Two-Sample Assuming Equal Variances

R4 Station 2	*Treated*	*Untreated*
Mean	-0.5235	-0.07025
Variance	0.142206	0.520075
Observations	4	4
Pooled Variance	0.33114	
Hypothesized Mean Difference	0	
df	6	
t Stat	-1.1139	
P(T<=t) two-tail	0.307943	
t Critical two-tail	2.446912	

Appendix R: Two-Sided t-Test Results for Contextual R3 and R4 LCC Data

Operator-Specific

t-Test: Two-Sample Assuming Equal Variances

R3 Operator A	*Treated*	*Untreated*
Mean	-0.53225	-0.2725
Variance	0.021421	0.021718
Observations	4	4
Pooled Variance	0.021569	
Hypothesized Mean Difference	0	
df	6	
t Stat	-2.50122	
P(T<=t) two-tail	0.046451	
t Critical two-tail	2.446912	

t-Test: Two-Sample Assuming Equal Variances

R3 Operator B	*Treated*	*Untreated*
Mean	-0.47725	-0.43225
Variance	0.055875	0.015777
Observations	4	4
Pooled Variance	0.035826	
Hypothesized Mean Difference	0	
df	6	
t Stat	-0.33622	
P(T<=t) two-tail	0.748149	
t Critical two-tail	2.446912	

t-Test: Two-Sample Assuming Equal Variances

R4 Operator A	*Treated*	*Untreated*
Mean	-0.499	-0.062
Variance	0.148955	0.533315
Observations	4	4
Pooled Variance	0.341135	
Hypothesized Mean Difference	0	
df	6	
t Stat	-1.05812	
P(T<=t) two-tail	0.330731	
t Critical two-tail	2.446912	

t-Test: Two-Sample Assuming Equal Variances

R4 Operator B	*Treated*	*Untreated*
Mean	-0.41225	-0.32
Variance	0.077867	0.070865
Observations	4	4
Pooled Variance	0.074366	
Hypothesized Mean Difference	0	
df	6	
t Stat	-0.4784	
P(T<=t) two-tail	0.649296	
t Critical two-tail	2.446912	

Appendix S: Paired t-Test Results for R1/R2 versus R3 Treated and Untreated Contextual Station-Specific LCC Data

t-Test: Paired Two Sample for Means

Treated Station 1	*R1/R2*	*R3*
Mean	-0.04073	-0.50125
Variance	0.002266	0.029728
Observations	4	4
Pearson Correlation	-0.4471	
Hypothesized Mean Difference	0	
df	3	
t Stat	4.644088	
P(T<=t) two-tail	0.018821	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Untreated Station 1	*R1/R2*	*R3*
Mean	-0.04025	-0.2665
Variance	0.000896	0.019918
Observations	4	4
Pearson Correlation	-0.03909	
Hypothesized Mean Difference	0	
df	3	
t Stat	3.111828	
P(T<=t) two-tail	0.052806	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Treated Station 2	*R1/R2*	*R3*
Mean	-0.03633	-0.50825
Variance	0.001119	0.049552
Observations	4	4
Pearson Correlation	-0.77142	
Hypothesized Mean Difference	0	
df	3	
t Stat	3.785796	
P(T<=t) two-tail	0.032315	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

UnTreated Station 2	*R1/R2*	*R3*
Mean	-0.04175	-0.43825
Variance	0.003093	0.014924
Observations	4	4
Pearson Correlation	-0.51961	
Hypothesized Mean Difference	0	
df	3	
t Stat	5.0076	
P(T<=t) two-tail	0.015328	
t Critical two-tail	3.182446	

Appendix T: Paired t-Test Results for R1/R2 versus R3 Treated and Untreated Contextual Operator-Specific LCC Data

t-Test: Paired Two Sample for Means

Treated Operator A	*R1/R2*	*R3*
Mean	-0.03948	-0.53225
Variance	0.001125	0.021421
Observations	4	4
Pearson Correlation	-0.66217	
Hypothesized Mean Difference	0	
df	3	
t Stat	5.782744	
P(T<=t) two-tail	0.010285	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Untreated Operator A	*R1/R2*	*R3*
Mean	-0.02725	-0.53225
Variance	0.001162	0.021421
Observations	4	4
Pearson Correlation	0.684001	
Hypothesized Mean Difference	0	
df	3	
t Stat	8.046	
P(T<=t) two-tail	0.00401	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Treated Operator B	*R1/R2*	*R3*
Mean	-0.04783	-0.47725
Variance	0.002347	0.055875
Observations	4	4
Pearson Correlation	-0.71342	
Hypothesized Mean Difference	0	
df	3	
t Stat	3.14528	
P(T<=t) two-tail	0.051453	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Untreated Operator B	*R1/R2*	*R3*
Mean	-0.05475	-0.43225
Variance	0.002324	0.015777
Observations	4	4
Pearson Correlation	-0.68316	
Hypothesized Mean Difference	0	
df	3	
t Stat	4.648905	
P(T<=t) two-tail	0.018768	
t Critical two-tail	3.182446	

Appendix U: Paired t-Test Results for R3 versus R4 Treated and Untreated Contextual Station-Specific LCC Data

t-Test: Paired Two Sample for Means

Treated Station 1	*R3*	*R4*
Mean	-0.50125	-0.38775
Variance	0.029728	0.077348
Observations	4	4
Pearson Correlation	-0.68318	
Hypothesized Mean Difference	0	
df	3	
t Stat	-0.5464	
P(T<=t) two-tail	0.622807	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Untreated Station 1	*R3*	*R4*
Mean	-0.2665	-0.31175
Variance	0.019918	0.089599
Observations	4	4
Pearson Correlation	-0.70481	
Hypothesized Mean Difference	0	
df	3	
t Stat	0.2201	
P(T<=t) two-tail	0.83992	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Treated Station 2	*R3*	*R4*
Mean	-0.50825	-0.5235
Variance	0.049552	0.142206
Observations	4	4
Pearson Correlation	-0.74604	
Hypothesized Mean Difference	0	
df	3	
t Stat	0.054171	
P(T<=t) two-tail	0.960205	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Untreated Station 2	*R3*	*R4*
Mean	-0.43825	-0.07025
Variance	0.014924	0.520075
Observations	4	4
Pearson Correlation	0.101875	
Hypothesized Mean Difference	0	
df	3	
t Stat	-1.02356	
P(T<=t) two-tail	0.381376	
t Critical two-tail	3.182446	

Appendix V: Paired t-Test Results for R3 versus R4 Treated and Untreated Contextual Operator-Specific LCC Data

t-Test: Paired Two Sample for Means

Treated Operator A	*R3*	*R4*
Mean	-0.53225	-0.499
Variance	0.021421	0.148955
Observations	4	4
Pearson Correlation	-0.96295	
Hypothesized Mean Difference	0	
df	3	
t Stat	-0.12586	
P(T<=t) two-tail	0.907803	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Untreated Operator A	*R3*	*R4*
Mean	-0.53225	-0.062
Variance	0.021421	0.533315
Observations	4	4
Pearson Correlation	0.932124	
Hypothesized Mean Difference	0	
df	3	
t Stat	-1.57744	
P(T<=t) two-tail	0.212797	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Treated Operator B	*R3*	*R4*
Mean	-0.47725	-0.41225
Variance	0.055875	0.077867
Observations	4	4
Pearson Correlation	-0.66006	
Hypothesized Mean Difference	0	
df	3	
t Stat	-0.27665	
P(T<=t) two-tail	0.800016	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Untreated Operator B	*R3*	*R4*
Mean	-0.43225	-0.32
Variance	0.015777	0.070865
Observations	4	4
Pearson Correlation	-0.05169	
Hypothesized Mean Difference	0	
df	3	
t Stat	-0.74793	
P(T<=t) two-tail	0.508797	
t Critical two-tail	3.182446	

Appendix W: Paired t-Test Results for R1/R2 versus R4 Treated and Untreated Contextual Station-Specific LCC Data

t-Test: Paired Two Sample for Means

Treated Station 1	*R1/R2*	*R4*
Mean	-0.04073	-0.38775
Variance	0.002266	0.077348
Observations	4	4
Pearson Correlation	0.913153	
Hypothesized Mean Difference	0	
df	3	
t Stat	2.947796	
P(T<=t) two-tail	0.060131	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Untreated Station 1	*R1/R2*	*R4*
Mean	-0.04025	-0.31175
Variance	0.000896	0.089599
Observations	4	4
Pearson Correlation	0.6757	
Hypothesized Mean Difference	0	
df	3	
t Stat	1.939471	
P(T<=t) two-tail	0.147788	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Treated Station 2	*R1/R2*	*R4*
Mean	-0.03633	-0.5235
Variance	0.001119	0.142206
Observations	4	4
Pearson Correlation	0.944559	
Hypothesized Mean Difference	0	
df	3	
t Stat	2.818618	
P(T<=t) two-tail	0.066815	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Untreated Station 2	*R1/R2*	*R4*
Mean	-0.04175	-0.07025
Variance	0.003093	0.520075
Observations	4	4
Pearson Correlation	0.610083	
Hypothesized Mean Difference	0	
df	3	
t Stat	0.082771	
P(T<=t) two-tail	0.939247	
t Critical two-tail	3.182446	

Appendix X: Paired t-Test Results for R1/R2 versus R4 Treated and Untreated Contextual Operator-Specific LCC Data

t-Test: Paired Two Sample for Means

Treated Operator A	*R1/R2*	*R4*
Mean	-0.03948	-0.499
Variance	0.001125	0.148955
Observations	4	4
Pearson Correlation	0.799586	
Hypothesized Mean Difference	0	
df	3	
t Stat	2.555078	
P(T<=t) two-tail	0.083572	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Untreated Operator A	*R1/R2*	*R4*
Mean	-0.02725	-0.062
Variance	0.001162	0.533315
Observations	4	4
Pearson Correlation	0.637381	
Hypothesized Mean Difference	0	
df	3	
t Stat	0.09802	
P(T<=t) two-tail	0.928099	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Treated Operator B	*R1/R2*	*R4*
Mean	-0.04783	-0.41225
Variance	0.002347	0.077867
Observations	4	4
Pearson Correlation	0.909446	
Hypothesized Mean Difference	0	
df	3	
t Stat	3.090326	
P(T<=t) two-tail	0.0537	
t Critical two-tail	3.182446	

t-Test: Paired Two Sample for Means

Untreated Operator B	*R1/R2*	*R4*
Mean	-0.05475	-0.32
Variance	0.002324	0.070865
Observations	4	4
Pearson Correlation	0.754516	
Hypothesized Mean Difference	0	
df	3	
t Stat	2.286675	
P(T<=t) two-tail	0.106281	
t Critical two-tail	3.182446	

Appendix Y: t-Test Results for Total Cycle Time (TCT) Data

R1 & R2 Two-Sample t-Test Results of Treated versus Untreated TCT Data

t-Test: Two-Sample Assuming Equal Variances

R1 & R2 TCT	*Treated*	*Untreated*
Mean	134.25	150
Variance	294.9167	544.6667
Observations	4	4
Pooled Variance	419.7917	
Hypothesized Mean Difference	0	
df	6	
t Stat	-1.08712	
P(T<=t) two-tail	0.318714	
t Critical two-tail	2.446912	

R1 & R2 Two-Sample t-Test Results of Treated versus Untreated TCT Data

OPA+OpB

t-Test: Two-Sample Assuming Equal Variances

R3 & R4 TCT Operator A+Operator B		*Untreated*
Mean	96.5	117.75
Variance	85.66667	141.5833
Observations	4	4
Pooled Variance	113.625	
Hypothesized Mean Difference	0	
df	6	
t Stat	-2.81927	
P(T<=t) one-tail	0.015192	
t Critical one-tail	1.94318	
P(T<=t) two-tail	0.030383	
t Critical two-tail	2.446912	

OPB+OpA

t-Test: Two-Sample Assuming Equal Variances

R3 & R4 TCT Operator B+Operator A		*Untreated*
Mean	92.25	123
Variance	20.25	308.6667
Observations	4	4
Pooled Variance	164.4583	
Hypothesized Mean Difference	0	
df	6	
t Stat	-3.39103	
P(T<=t) two-tail	0.014657	
t Critical two-tail	2.446912	

Paired t-Test Results of Treated TCT Data

R1/R2 to R3

t-Test: Paired Two Sample for Means

Treated TCT	*R1 & R2*	*R3*
Mean	134.25	99.25
Variance	294.9167	50.25
Observations	4	4
Pearson Correlation	0.155391	
Hypothesized Mean Difference	0	
df	3	
t Stat	3.992944	
P(T<=t) two-tail	0.028138	
t Critical two-tail	3.182446	

R1/R2 to R4

t-Test: Paired Two Sample for Means

Treated TCT	*R1 & R2*	*R4*
Mean	134.25	89.5
Variance	294.9167	4.333333
Observations	4	4
Pearson Correlation	-0.64804	
Hypothesized Mean Difference	0	
df	3	
t Stat	4.81445	
P(T<=t) two-tail	0.017068	
t Critical two-tail	3.182446	

R3 to R4

t-Test: Paired Two Sample for Means

Treated TCT	*R3*	*R4*
Mean	99.25	89.5
Variance	50.25	4.333333
Observations	4	4
Pearson Correlation	0.463077	
Hypothesized Mean Difference	0	
df	3	
t Stat	3.048488	
P(T<=t) two-tail	0.055494	
t Critical two-tail	3.182446	

Two-Sample t-Test Results for Treated and Untreated TCT Data

R3

t-Test: Two-Sample Assuming Equal Variances

R3 TCT	*Treated*	*Untreated*
Mean	99.25	126
Variance	50.25	211.3333
Observations	4	4
Pooled Variance	130.7917	
Hypothesized Mean Difference	0	
df	6	
t Stat	-3.30787	
P(T<=t) two-tail	0.016248	
t Critical two-tail	2.446912	

R4

t-Test: Two-Sample Assuming Equal Variances

R4 TCT	*Treated*	*Untreated*
Mean	89.5	114.75
Variance	4.333333	172.9167
Observations	4	4
Pooled Variance	88.625	
Hypothesized Mean Difference	0	
df	6	
t Stat	-3.79313	
P(T<=t) two-tail	0.00904	
t Critical two-tail	2.446912	

Appendix Z: t-Test Results for Total Throughput Time (TPT) Data

Two-Sample t-Test Results of Treated versus Untreated TPT

R1/R2

t-Test: Two-Sample Assuming Equal Variances

R1 & R2 TPT	*Treated*	*Untreated*
Mean	152.5	176
Variance	953	896
Observations	4	4
Pooled Variance	924.5	
Hypothesized Mean Difference	0	
df	6	
t Stat	-1.09302	
P(T<=t) two-tail	0.316314	
t Critical two-tail	2.446912	

R3/R4

t-Test: Two-Sample Assuming Equal Variances

R3 & R4 TPT	*Treated*	*Untreated*
Mean	103.5	137.5
Variance	150.3333	137
Observations	4	4
Pooled Variance	143.6667	
Hypothesized Mean Difference	0	
df	6	
t Stat	-4.01158	
P(T<=t) two-tail	0.007026	
t Critical two-tail	2.446912	

Paired t-Test Results of Treated and Untreated TPT Data

Treated R1/R2 to R3/R4

t-Test: Paired Two Sample for Means

Treated TPT: R1/R2 to R3/R4	*R1&R2*	*R3&R4*
Mean	152.5	103.5
Variance	953	150.3333
Observations	4	4
Pearson Correlation	-0.30559	
Hypothesized Mean Difference	0	
df	3	
t Stat	2.6825	
P(T<=t) two-tail	0.07489	
t Critical two-tail	3.182446	

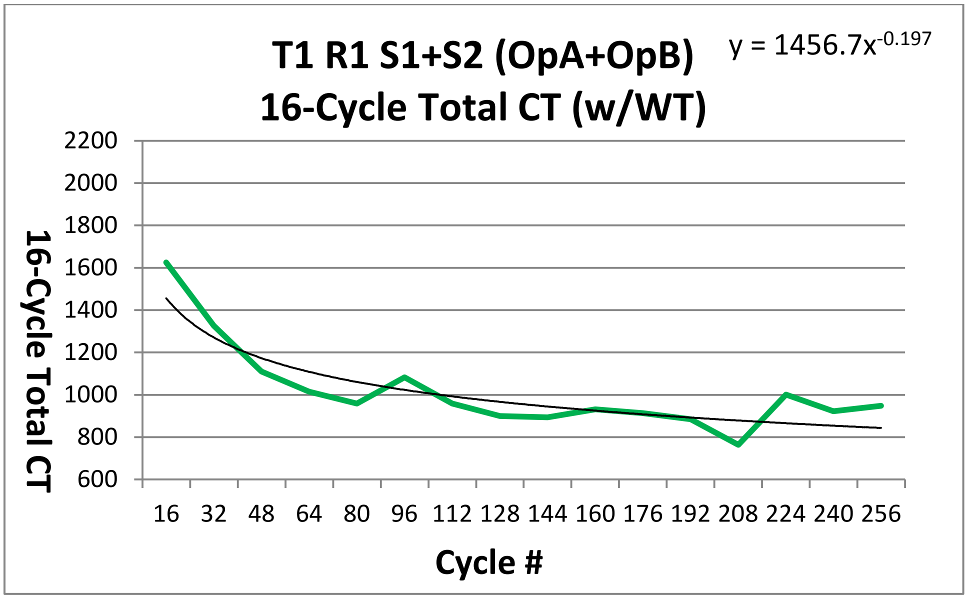
Untreated R1/R2 to R3/R4

t-Test: Paired Two Sample for Means

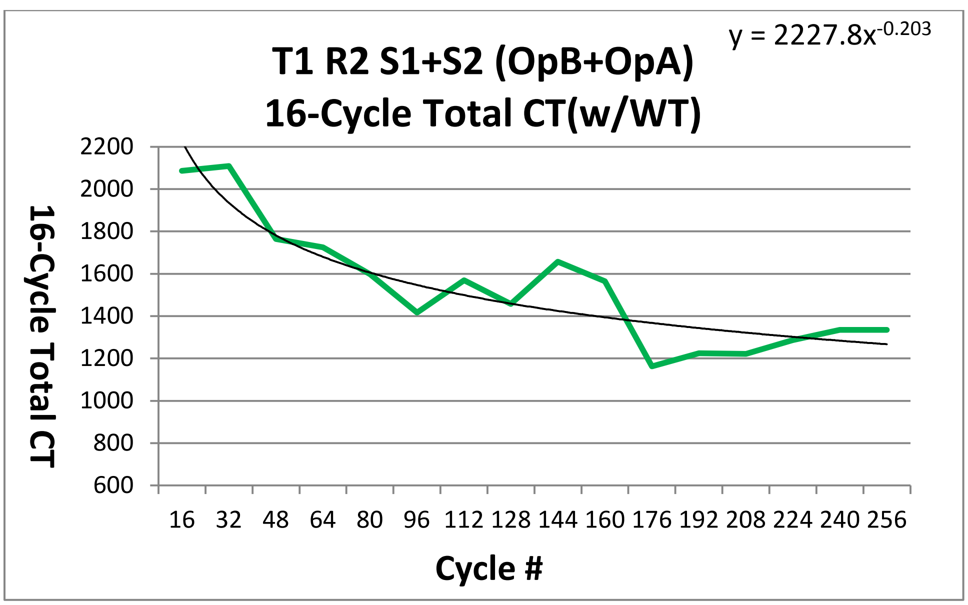
Untreated TPT: R1/R2 to R3/R4	*R1&R2*	*R3&R4*
Mean	176	137.5
Variance	896	137
Observations	4	4
Pearson Correlation	0.395784	
Hypothesized Mean Difference	0	
df	3	
t Stat	2.801081	
P(T<=t) two-tail	0.067792	
t Critical two-tail	3.182446	

Appendix AA: 16-Cycle Total Throughput (TPT) Learning Curves

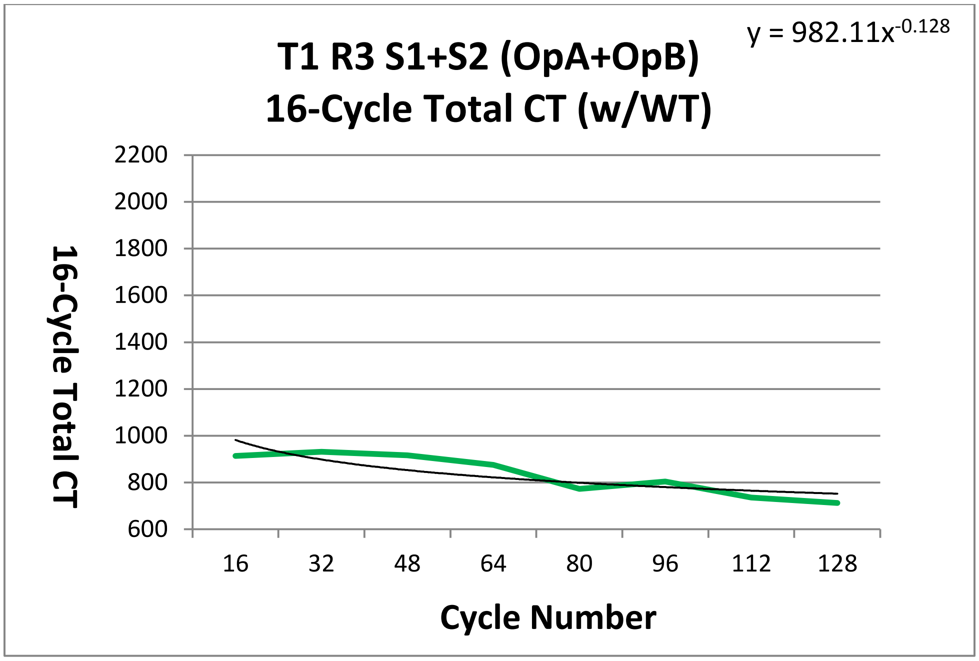
Team 1 - R1



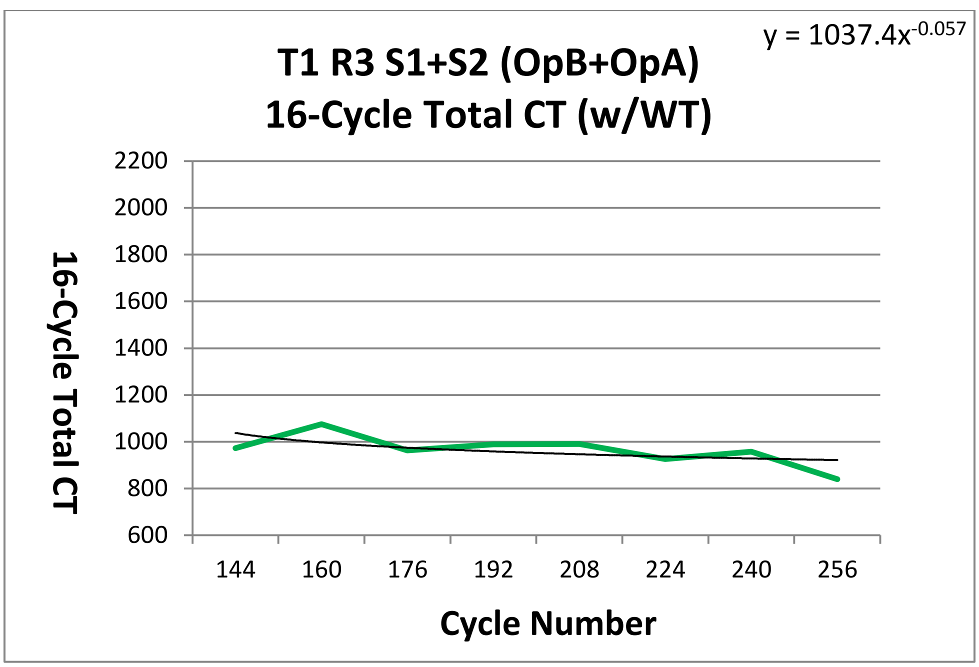
Team 1 - R2



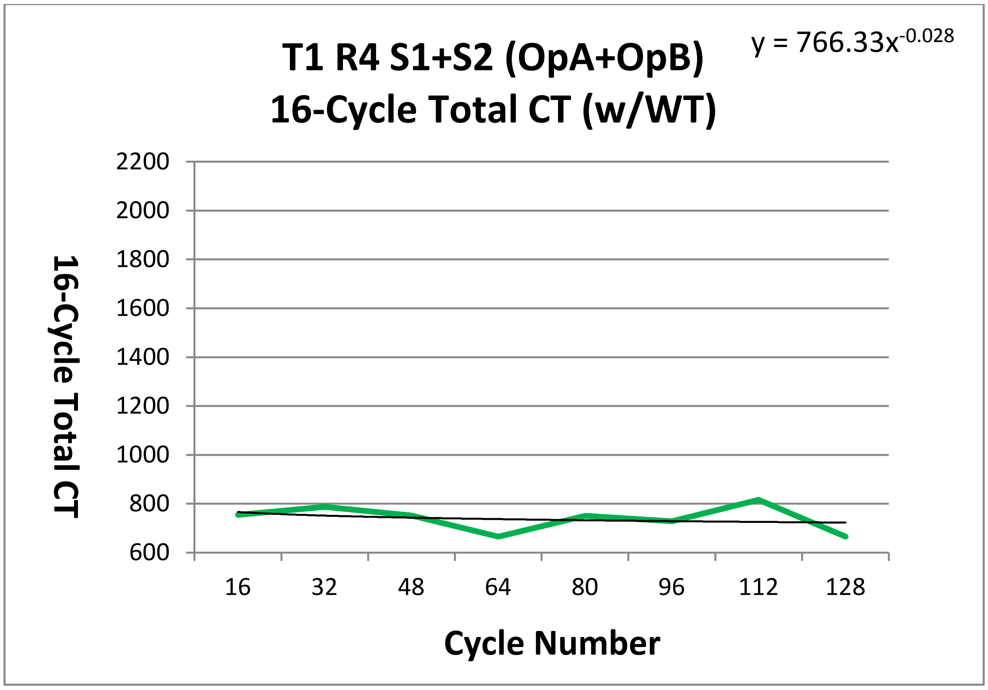
Team 1 - Operator A + Operator B- R3



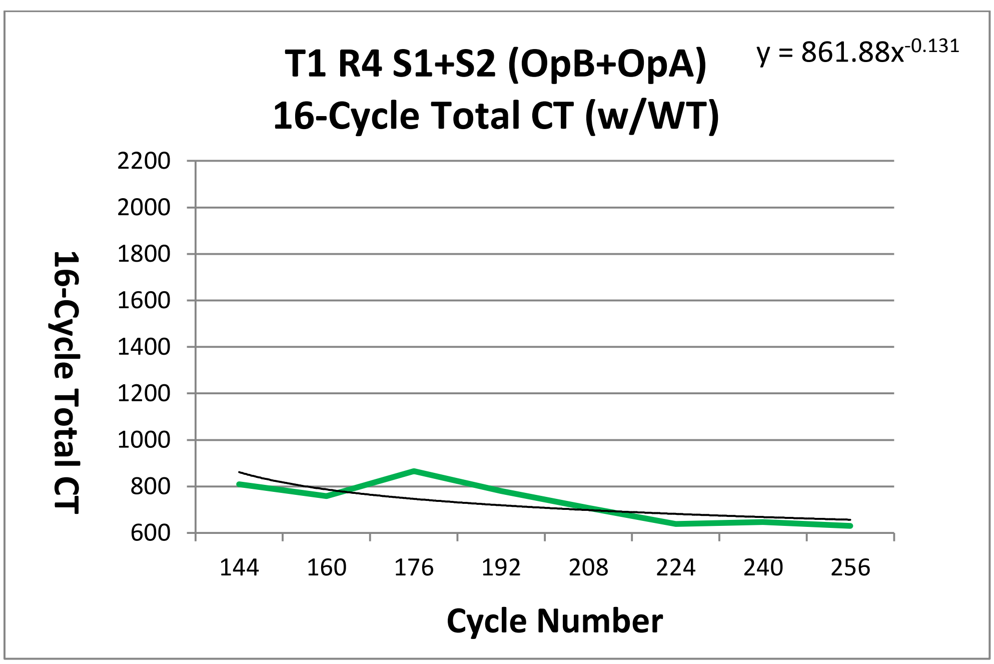
Team 1 - Operator B + Operator A - R3



Team 1 - Operator A + Operator B - R4

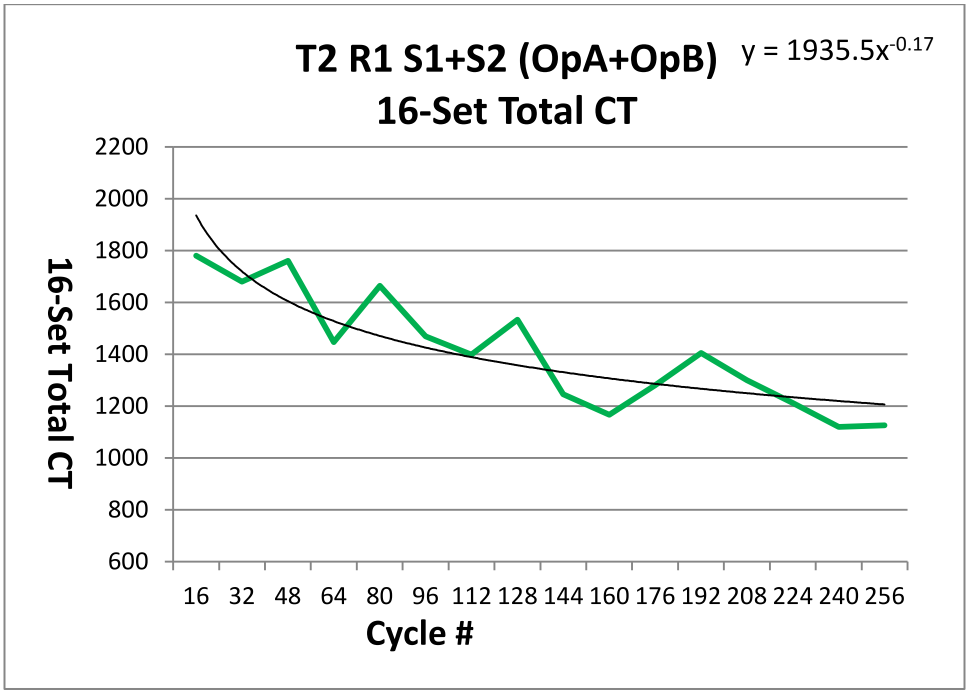


Team 1 - Operator B + Operator A – R4

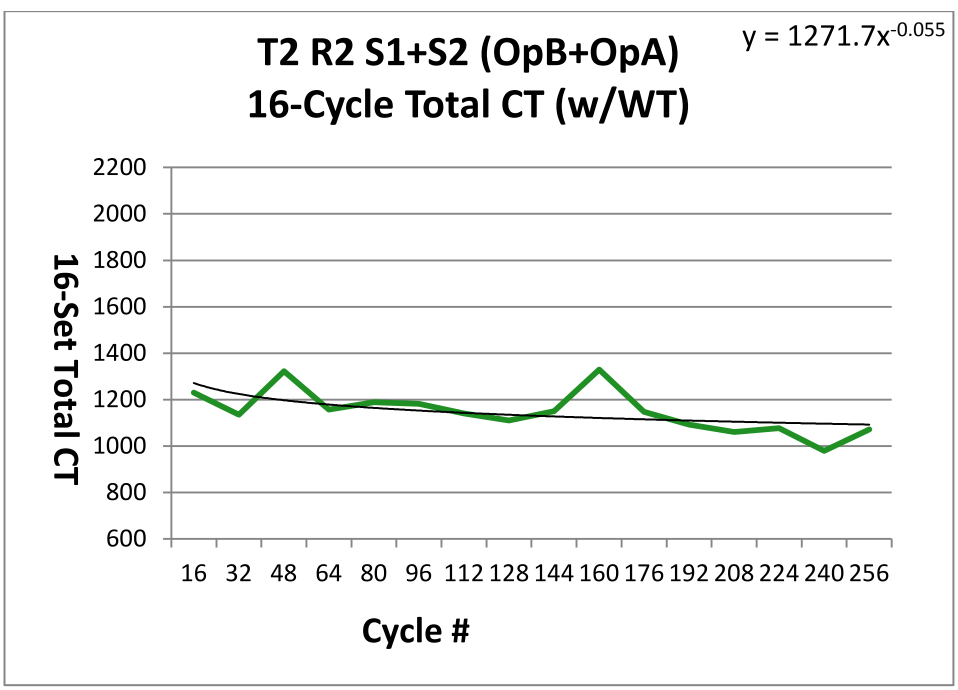


Team 2

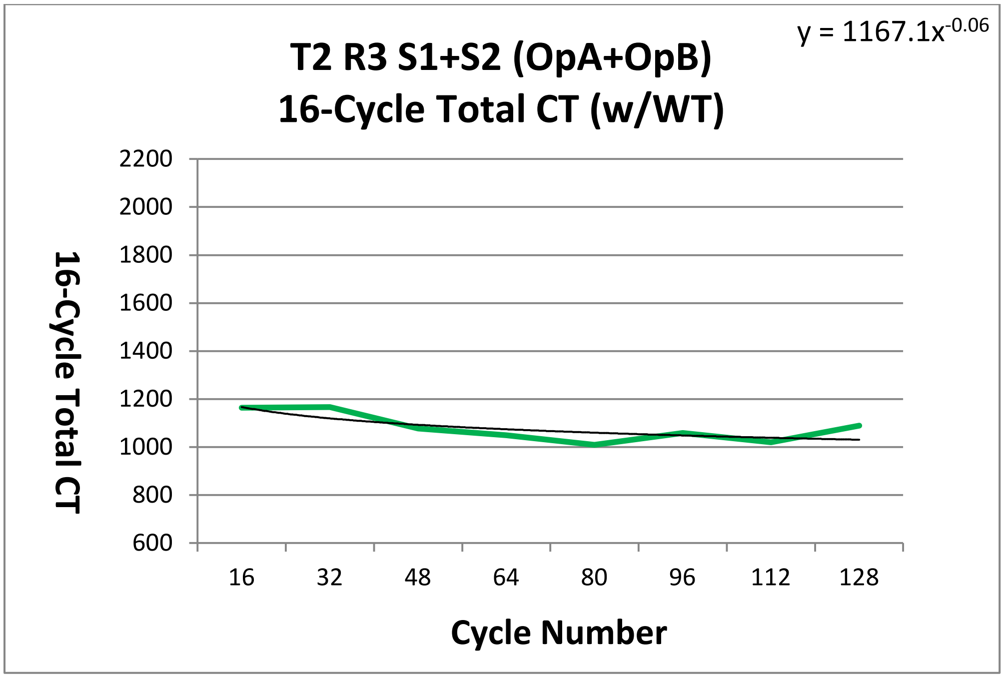
Team 2 – R



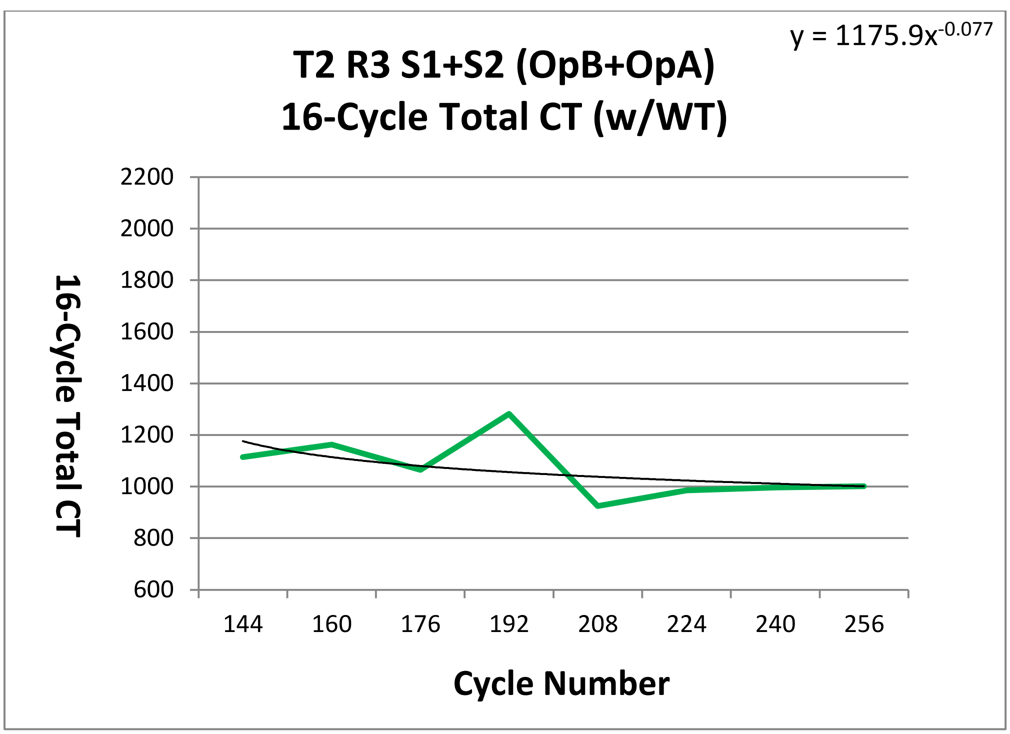
Team 2 - R2



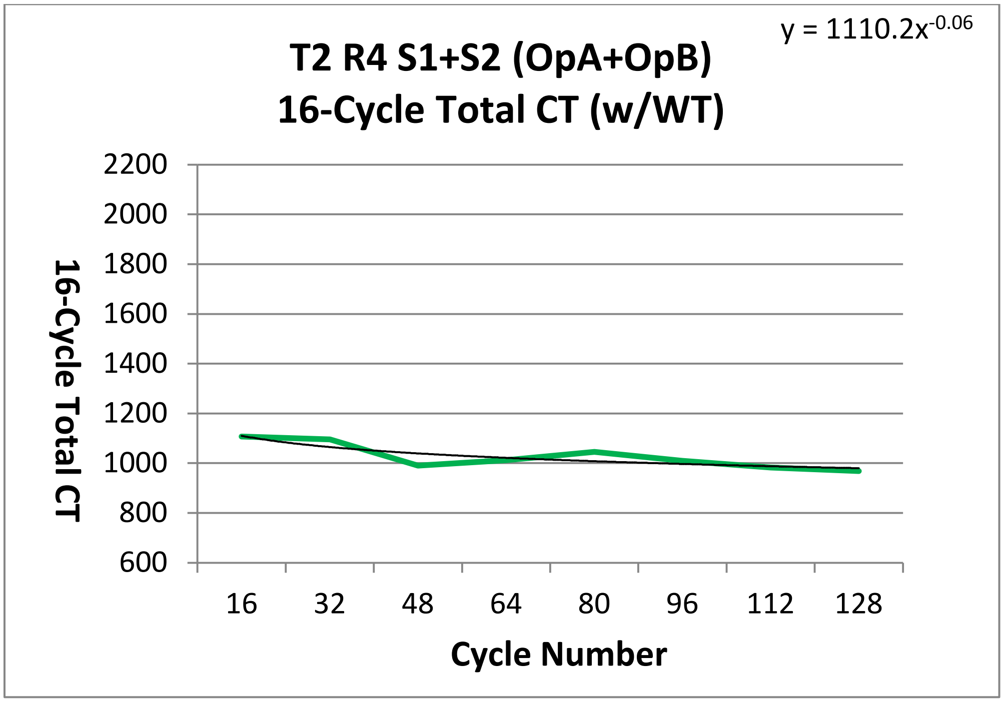
Team 2 - Operator A + Operator B – R3



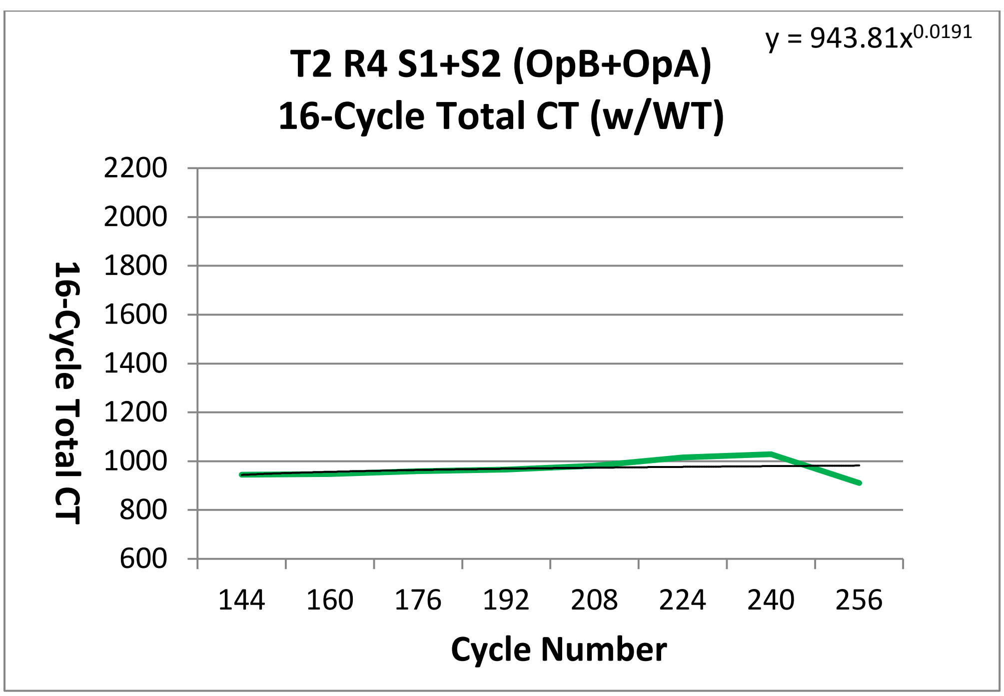
Team 2 - Operator B + Operator A – R3



Team 2 - Operator A + Operator B – R4

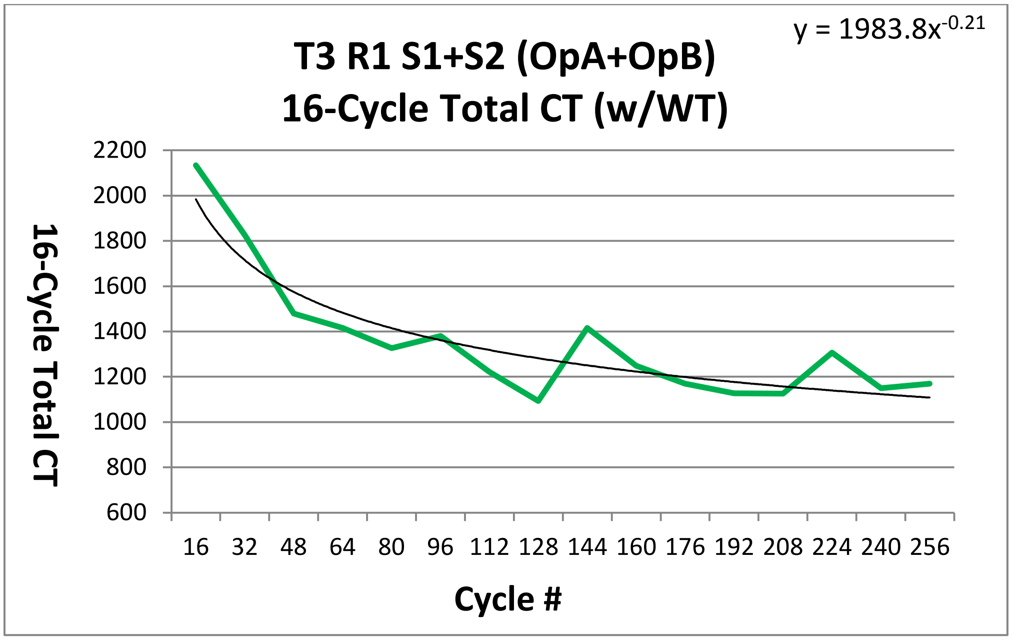


Team 2 - Operator B + Operator A – R4

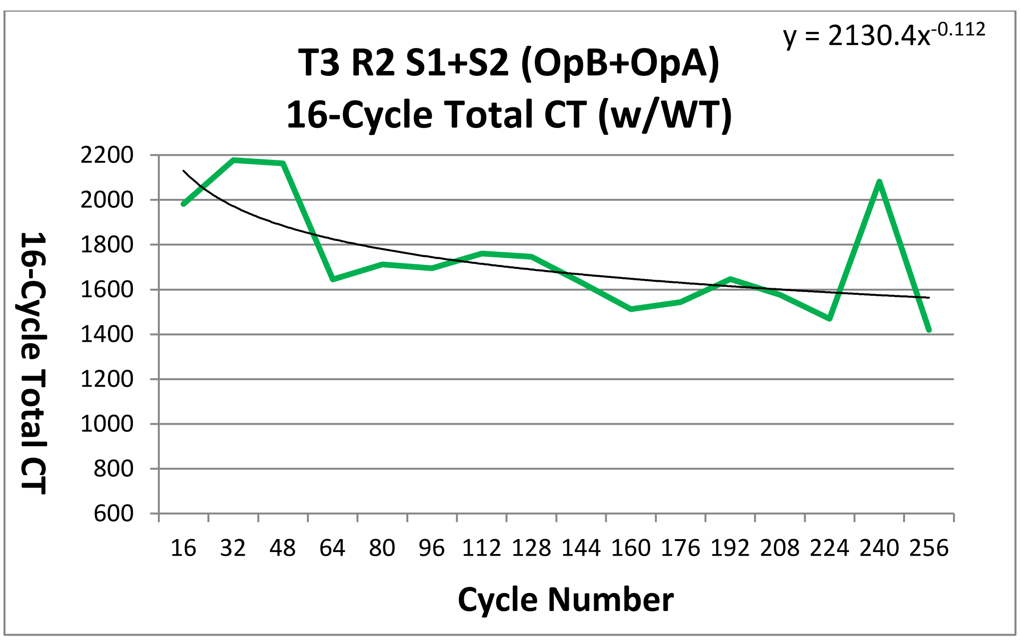


Team 3

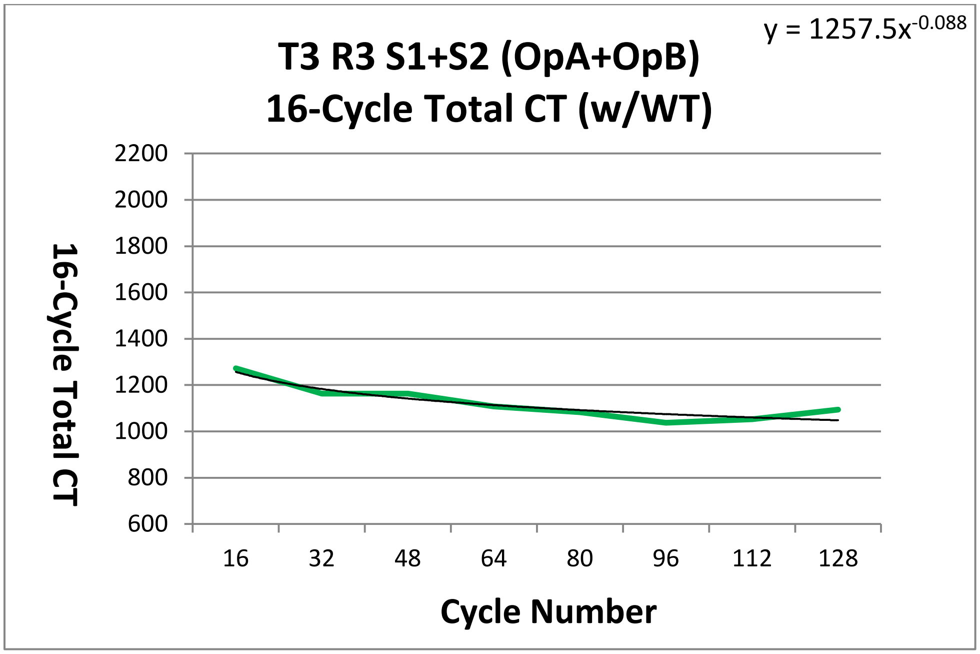
Team 3 - R1



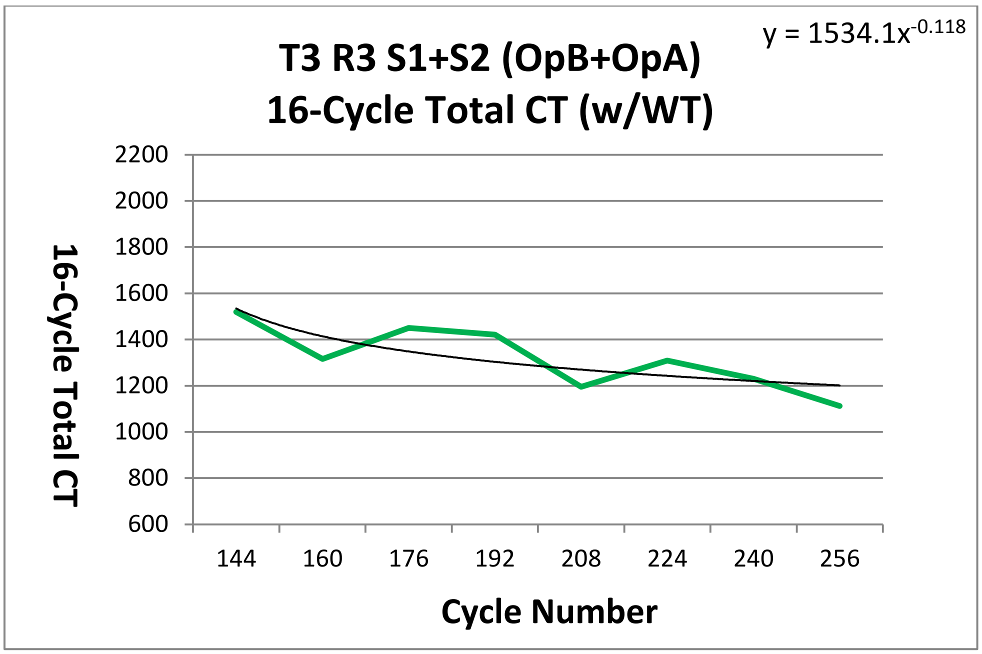
Team 3 – R2



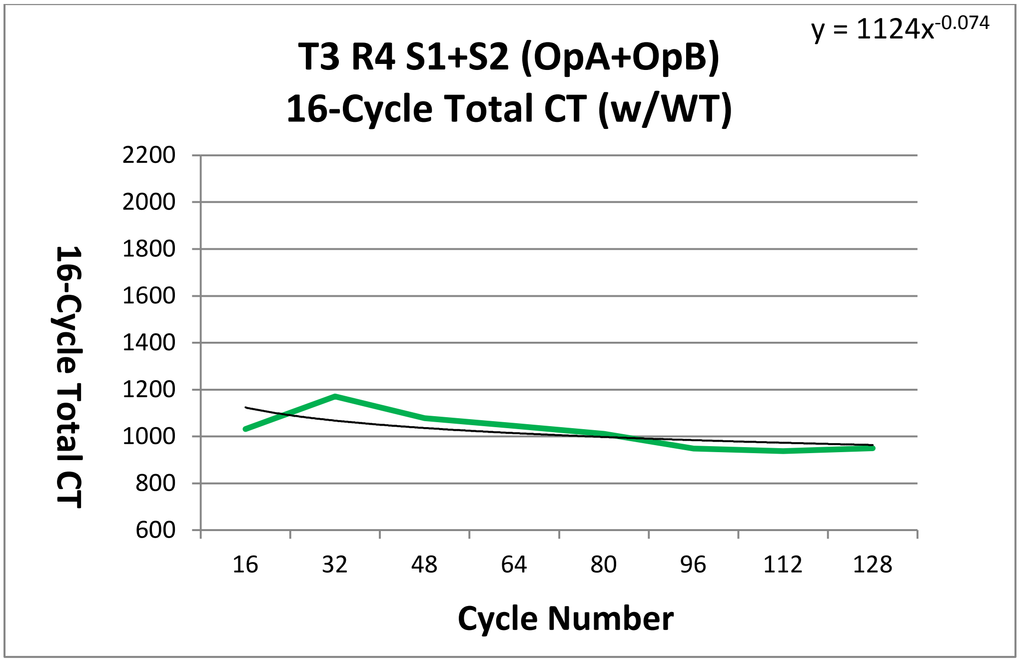
Team 3 – Operator A + Operator B – R3



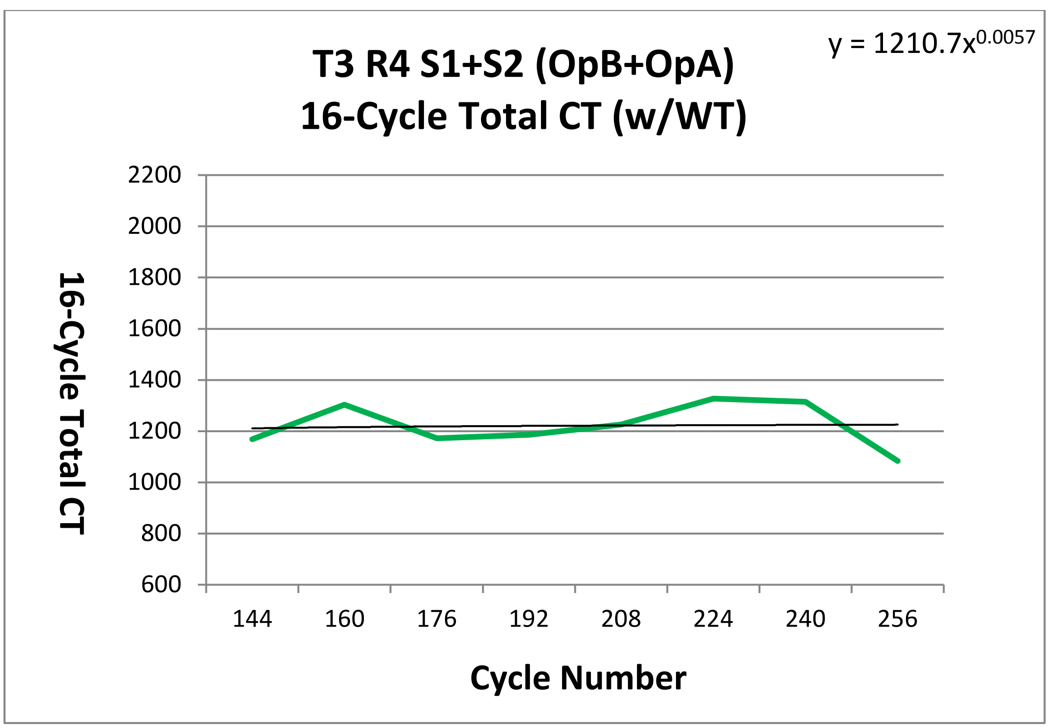
Team 3 – Operator B + Operator A – R3



Team 3 – Operator A + Operator B – R4

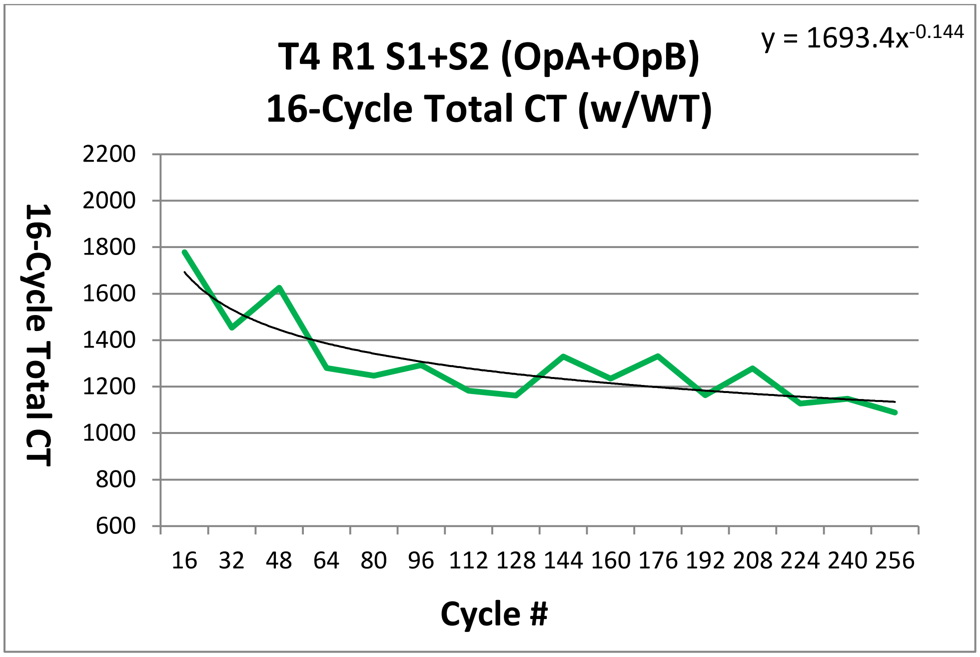


Team 3 – Operator B + Operator A + R4

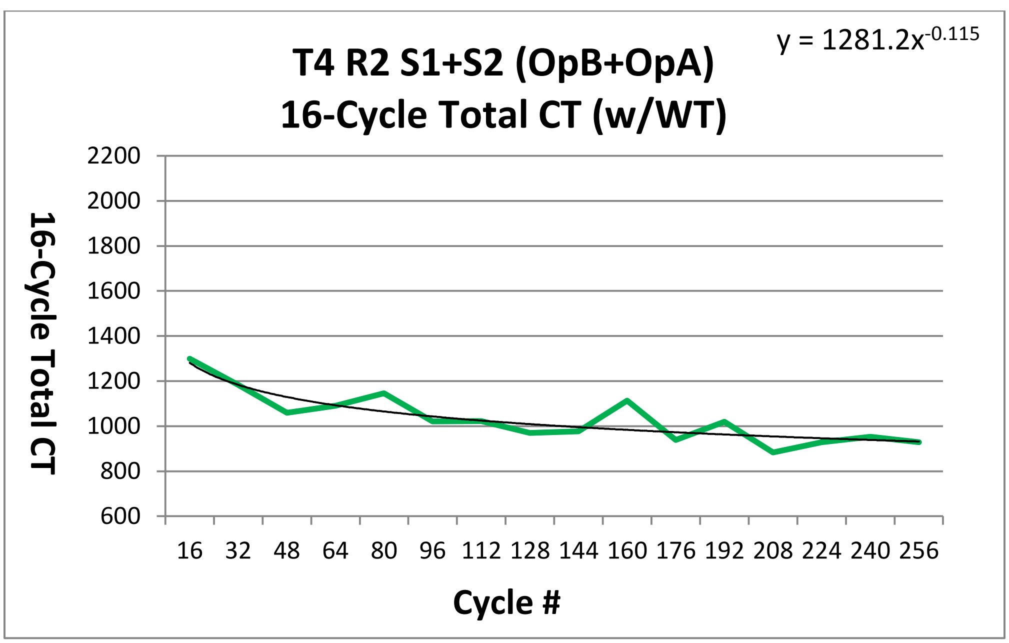


Team 4

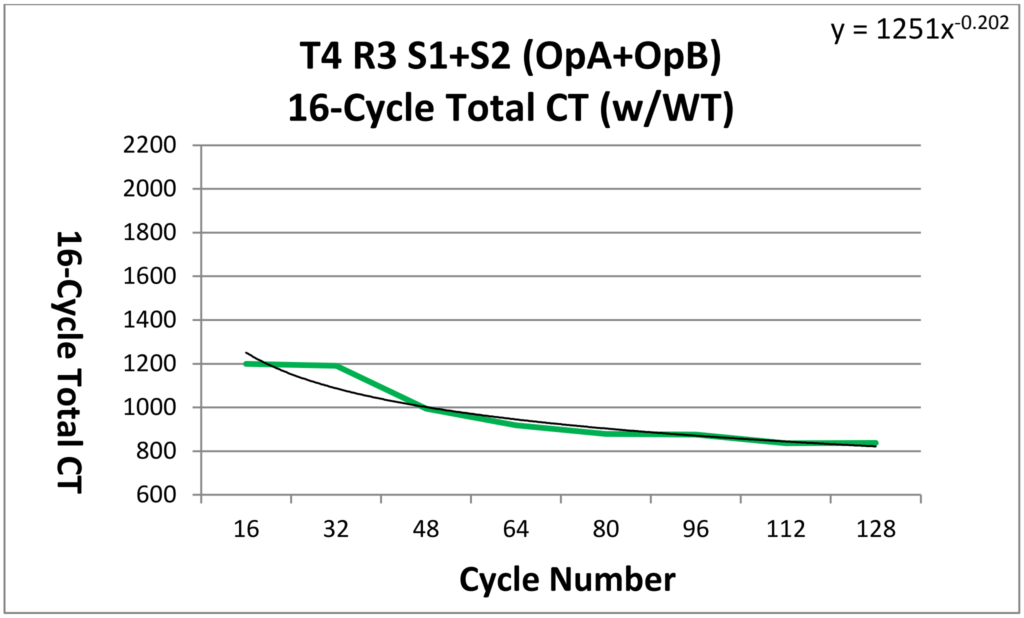
Team 4 - R1



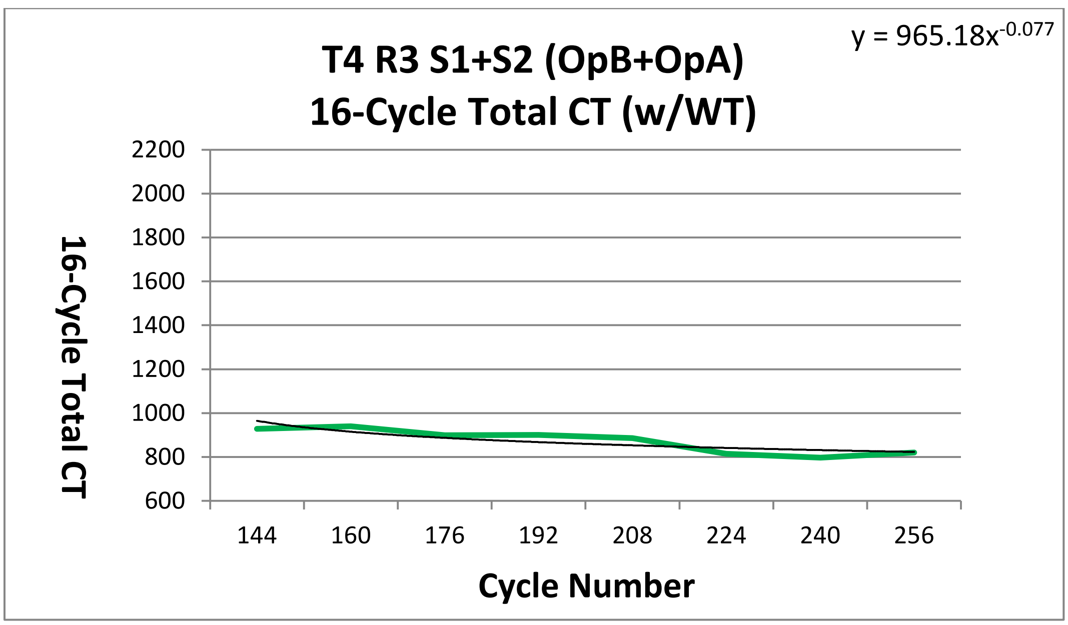
Team 4 – R2



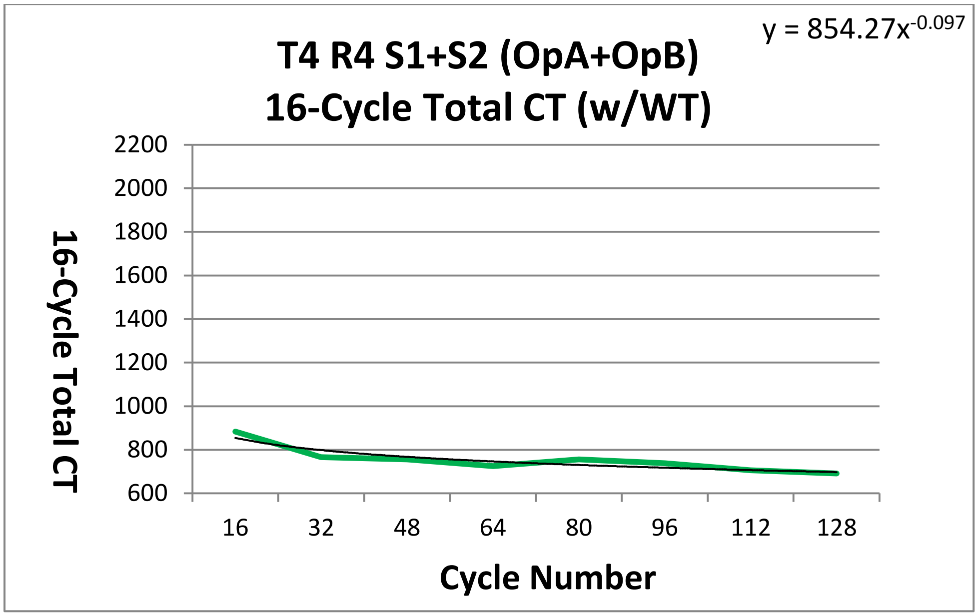
Team 4 – Operator A + Operator B – R3



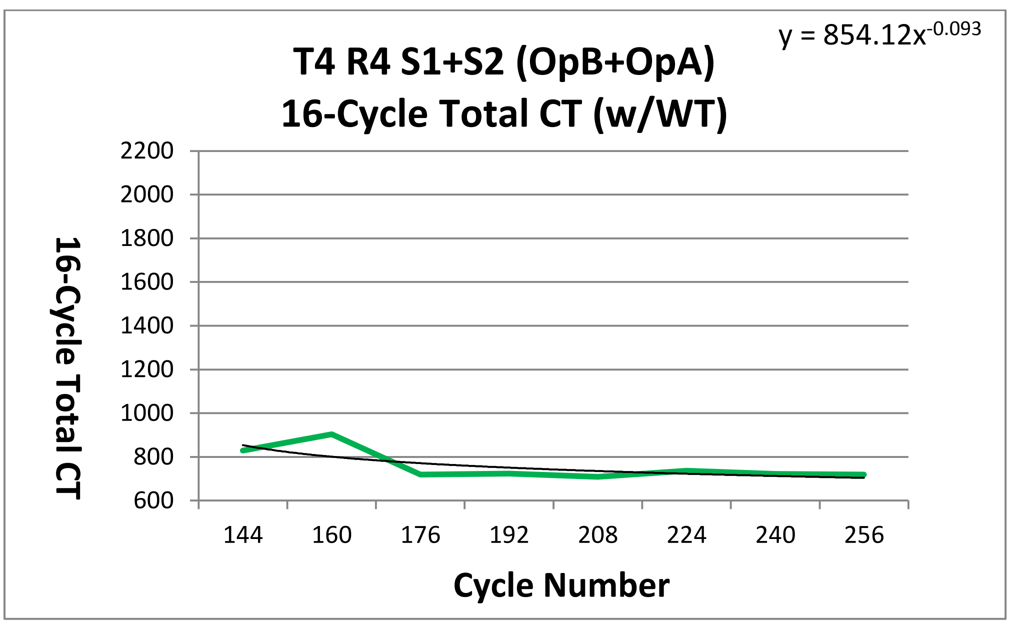
Team 4 – Operator B + Operator A – R3



Team 4 – Operator A + Operator B – R4



Team 4 – Operator B + Operator A – R4



Appendix BB: Two-Sample t-Test Analysis Results of Treated vs Untreated TPT

LCC Results

R1/R2

t-Test: Two-Sample Assuming Equal Variances

R1 & R2 TPT	*Treated*	*Untreated*
Mean	152.5	176
Variance	953	896
Observations	4	4
Pooled Variance	924.5	
Hypothesized Mean Difference	0	
df	6	
t Stat	-1.09302	
P(T<=t) two-tail	0.316314	
t Critical two-tail	2.446912	

R3/R4

t-Test: Two-Sample Assuming Equal Variances

R3 & R4 TPT	*Treated*	*Untreated*
Mean	103.5	137.5
Variance	150.3333	137
Observations	4	4
Pooled Variance	143.6667	
Hypothesized Mean Difference	0	
df	6	
t Stat	-4.01158	
P(T<=t) two-tail	0.007026	
t Critical two-tail	2.446912	

Appendix CC: Paired t-Test Analysis Results of TPT LCC Results

Untreated R1/R2 to R3/R4

t-Test: Paired Two Sample for Means

Untreated TPT: R1/R2 to R3/R4	*R1&R2*	*R3&R4*
Mean	176	137.5
Variance	896	137
Observations	4	4
Pearson Correlation	0.395784	
Hypothesized Mean Difference	0	
df	3	
t Stat	2.801081	
P(T<=t) two-tail	0.067792	
t Critical two-tail	3.182446	

Treated R1/R2 to R3/R4

t-Test: Paired Two Sample for Means

Treated TPT: R1/R2 to R3/R4	*R1&R2*	*R3&R4*
Mean	152.5	103.5
Variance	953	150.3333
Observations	4	4
Pearson Correlation	-0.30559	
Hypothesized Mean Difference	0	
df	3	
t Stat	2.6825	
P(T<=t) two-tail	0.07489	
t Critical two-tail	3.182446	

Appendix DD: Standard Forms for LC Experimental Runs

R1 and R2 Starting Conditions

Starting condition: Runs 1 & 2

***Station 1** has parts for the first 4 units (delivered to Assembly)*

Lube, 2 charged nut drivers, tightening fixture, nuts and washers, stopwatch and CT log

***Station 2** has 4 un-assembled units PLUS loose parts for 8 more units and Master Production Sequence, stopwatch and CT and Defect log*

Each station works independently and stops for assessment at the end of each 16 cycle (unit) set. Wait for each other to catch up (1st station to stop measures WT till the other station stops) before beginning next 16 cycle set. The starting WIP is set using the RED cards.

Station 1: Assembly (build one at a time) (CT for 1)

1. *Start stopwatch*
2. ID appropriate variant to build from PC card (stays with unit)
3. Lube piston head sub-assembly O'ring and insert into correct tube
4. Assemble tube/rod sub-assembly
    a. Place bolts into bottom plate and set upright in work area
    b. Slide top plate onto tube/rod sub-assembly and insert onto bottom plate bolts
    c. Place washers and nuts onto tapped bolt ends
5. Tighten nuts, place with PC card into F/G area
6. *Lap stopwatch*
7. If no parts are available *Lap stopwatch* and note as separate WT element

Begin next cycle

Station 2: QA/Disassembly/WH/MH (build one at a time) (CT for 1)

1. *Start stop watch*
2. Conduct Quality check of the next unit
    a. Check for Quality defects and report PC # and defect
        i. Match PC card (sequence number) to Master sequence number and type
        ii. Check for Loose nuts
        iii. Check piston function (manually move up and down)
        iv. Check for aligned ports
        v. Check that height is correct and plates are level
3. Dismantle unit and wipe lube off plates, pistons and O'rings (do not remove the small O'rings from the plates), and restock next unit and place into Station 1 WIP inventory
4. *Lap stopwatch*
5. If no parts are available *Lap stopwatch* and note as separate WT element

Begin next cycle

Parts Per Unit

Small (RED)	Medium (GREEN)	Large (BLUE)
1) 1 ½" short upright tube	1) 2" medium upright tube	1) 2" tall upright tube
1) small top plate w/ O'ring	1) large top plate w/ O'ring	1) large top plate w/ O'ring
1) small bottom plate w/ O'ring	1) large bottom plate w/ O'ring	1) large bottom plate w/ O'ring
1) small piston head w/ short rod	1) large piston head w/ medium rod	1) large piston head w/ tall rod
4) short bolts	4) medium bolts	4) long bolts

Record outbound WIP and WT at each 16-unit cycle

R3 and R4 Starting Conditions

Starting condition: Runs 3 & 4 (STW, Waste Elimination and Systematic P/S)

<u>Station 1</u> has bins with parts for the first 2 units in WIP buffer

Lube, 2 charged nut drivers, tightening fixture, nuts and washers, stopwatch and CT log

<u>Station 2</u> has 4 assembled units in WIP buffer PLUS loose parts for 8 more units and Master Production Sequence, stopwatch and CT and Defect log

Each station works independently using the STW provided and stops for assessment at the end of each 16 cycle (unit) set. Wait for each other to catch up (1st station to stop measures WT till the other station stops) before beginning next 16 cycle set together. The starting WIP is set using the RED cards.

Use STW written at end of R3 (begin with alternating operator)

Rotate after 128 cycles

Station 1: Assembly (build one at a time) (CT for 1)

1. *Start stopwatch*
2. ID appropriate variant to build from PC card (stays with unit)
3. Lube piston head sub-assembly O'ring and insert into correct tube
4. Assemble tube/rod sub-assembly
   a. Place bolts into bottom plate and set upright in work area
   b. Slide top plate onto tube/rod sub-assembly and insert onto bottom plate bolts
   c. Place washers and nuts onto tapped bolt ends
5. Tighten nuts, place with PC card into F/G area
6. *Lap stopwatch*
7. If no parts are available *Lap stopwatch* and note as separate WT element

Begin next cycle

Station 2: QA/Disassembly/WH/MH (build one at a time) (CT for 1)

1. *Start stop watch*
2. Conduct Quality check of the next unit
   a. Check for Quality defects and report PC # and defect
      i. Match PC card (sequence number) to Master sequence number and type
      ii. Check for Loose nuts
      iii. Check piston function (manually move up and down)
      iv. Check for aligned ports
      v. Check that height is correct and plates are level
3. Dismantle unit and wipe lube off plates, pistons and O'rings (do not remove the small O'rings from the plates), and restock next unit and place into Station 1 WIP inventory
4. *Lap stopwatch*
5. If no parts are available *Lap stopwatch* and note as separate WT element

Begin next cycle

Parts Per Unit

Small (RED)	Medium (GREEN)	Large (BLUE)
1) 1 ½" short upright tube	1) 2" medium upright tube	1) 2" tall upright tube
1) small top plate w/ O'ring	1) large top plate w/ O'ring	1) large top plate w/ O'ring
1) small bottom plate w/ O'ring	1) large bottom plate w/ O'ring	1) large bottom plate w/ O'ring
1) small piston head w/ short rod	1) large piston head w/ medium rod	1) large piston head w/ tall rod
4) short bolts	4) medium bolts	4) long bolts

Measure WIP and WT at each 16-unit cycle
Mark each cycle with abnormal work
P/S station with highest CT after each 16 unit cycle
Fill out assessment including ID waste and potential CT reduction

Station 1 Cycle Time Log Sheet (all teams)

Station 1

pg 1/16

Cycle Time (CT) Log

Team #_______ Run #: 1 2 3 4

Operator____________________ Date_________

Cycle	CT	Comments
1		
2		
3		
4		
5		
6		
7		
8		
9		
10		
11		
12		
13		
14		
15		
16	WT	

Station 2 Cycle Time and Defect Log Sheet (all teams R1 & R2)

Station 2

pg 1/16

Cycle Time (CT) & Defect Log

Team #______ Run # 1 2

Operator____________________ Date__________

Cycle	CT	Defect Type	Comments
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			
11			
12			
13			
14			
15			
16	WT	WIP	

Station 2 Cycle Time & Defect Log Sheet (R3 & R4 treated teams)

Station 2

pg 1/16

Cycle Time (CT) & Defect Log

Team #______

Run #: 3 4

Operator____________________

Date_________

Cycle	CT	Defect Type	Abnormality	Comments
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				
11				
12				
13				
14				
15				
16				
	WT	WIP		

R1 and R2 Assessment Sheet (All Operators--Also Used for Untreated Teams R3 and R4)

Run 1 or 2

Work Assessment for Cylinder Factory (rev 050611)

Operator:________________________________ **Team #**________

Date:______________________ **Station (circle one): 1 2**

Run Number (circle one): 1 2 **Cumulative Cycle number (circle one below):**

16 32 48 64 80 96 112 128 144 160 176 192 208 224 240 256

1. Please identify all problems, work-a-rounds (if any), and improvement opportunities for your work during this 16-unit cycle. Rank the immediate impact on the system for both productivity and quality using a scale of 1 (most negative), 5 (no affect) and 10 (most positive) in the appropriate column.

Problems: Challenges to doing daily work		Immediate Impact on System	
		Productivity	Quality
No.			
Work-A-Rounds: A way to bypass a recognized problem doing daily work		Immediate Impact on System	
		Productivity	Quality
No.			
Improvement Opportunities: Things to make the work better		Immediate Impact on System	
		Productivity	Quality
No.			

Please Rank on a scale of 10 (very burdensome or stressful), 5 (neutral), 1 (extremely easy to perform or totally stress free)

Physical Burden: 1 2 3 4 5 6 7 8 9 10

Mental Burden: 1 2 3 4 5 6 7 8 9 10

Rank on scale of 1-5 your attitude towards your work (1=bored, 3=somewhat interested, 5=fully engaged)
Please circle one: 1 2 3 4 5

R3 and R4 Assessment Sheet for Treated Team Operators

Run 3 & 4

Work Assessment for Cylinder Factory (rev 050611)

Operator:________________________________ **Team #**________

Date:______________________ **Station (circle one): 1 2**

Run Number: 3 **Cumulative Cycle number (circle one below):**

16 32 48 64 80 96 112 128 144 160 176 192 208 224 240 256

1. Please identify all problems, work-a-rounds (if any), and improvement opportunities for your work during this 16-unit cycle. Rank the immediate impact on the system for both productivity and quality using a scale of 1 (most negative), 5 (no affect) and 10 (most positive) in the appropriate column.

Challenges to doing standard work and observed waste		Immediate Impact on System	
		Productivity	Quality
No.			

Adjustments to eliminate abnormal conditions doing standard work		Immediate Impact on System	
		Productivity	Quality
No.			

Improvement Opportunities: Things to make my standard work better		Immediate Impact on System	
		Productivity	Quality
No.			

Please Rank on a scale of 1 (very burdensome or stressful), 5 (neutral), 10 (extremely easy to perform or totally stress free)

Physical Burden: 1 2 3 4 5 6 7 8 9 10

Mental Burden: 1 2 3 4 5 6 7 8 9 10

Rank on scale of 1-5 your attitude towards your work (1=bored, 3=somewhat interested, 5=fully engaged)
Please circle one: 1 2 3 4 5

Observer / Supervisor Role

Observer/Supervisor Role

The O/S primary role is to keep the operators on track. The Operators roles in R1 and R2 are to work independently of each other and to do whatever it takes to get their jobs done.

Do not interfere, make suggestions or in any way assist the operators to perform their work.

Specific O/S tasks include;

- Use the stopwatch provided to track the total time for both operators to complete each 16-unit cycle set.
- Assist operators as needed for immediate safety issues.
- Contact me regarding safety, operational or equipment questions .
- Ensure the Operator Assessments are completed at the end of each 16-cycle set.
    - Problems, work-arounds, improvement ideas,
    - attitude rating, physical and mental burden rating.
- Ensure the operators start each 16-cycle set together.
- Input data as it received at the end of each 16-cycle set.
    - Use the excel template provided to input;
    - CT, defects and problems
    - Complete the O/S Record Sheet for each 16-cycle set.
        - **Total problem solving (P/S) is only tracked in R3 & R4**

Materials needed:

- Stopwatch to track total CT and P/S time
- O/S Report Table
- Laptop with excel template file
- calculator

Observer / Supervisor Report Table

Observer/Supervisor Report Table

Team #______

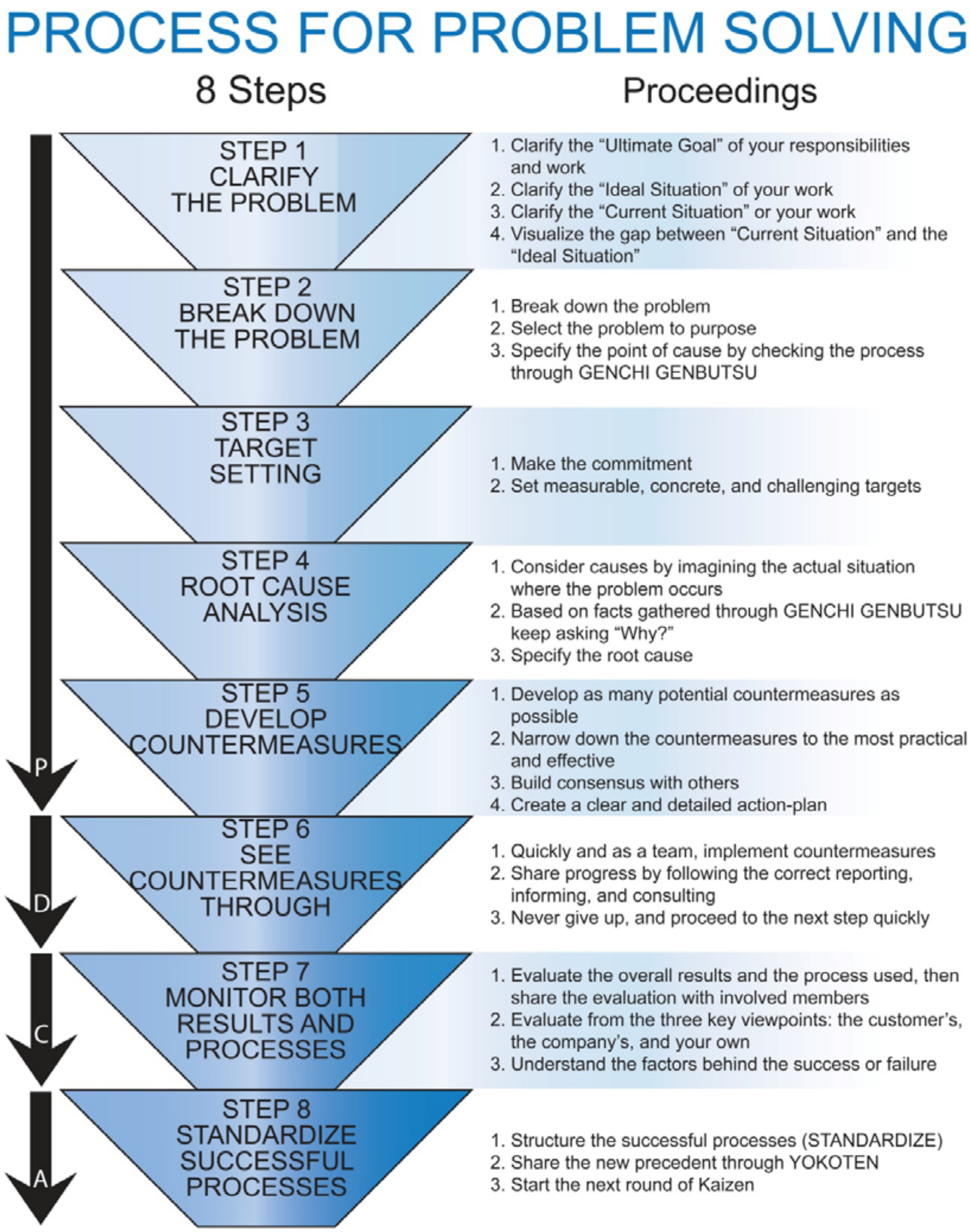
Run # 1 2 3 4

Observer/Supervisor:____________________

Date__________

Set #	Last Cycle #	Total CT (including WT)	WT/WIP/ Station	Total Defects	Total P/S Time
1	16				
2	32				
3	48				
4	64				
5	80				
6	96				
7	112				
8	128				
9	144				
10	160				
11	176				
12	192				
13	208				
14	224				
15	240				
16	256				

Appendix EE: Toyota's Systematic 8-Step Problem Solving Process



Appendix FF: Internal Review Board Approval Letter

UK
KENTUCKY

Office of Research Integrity
IRB, IACUC, RDRC
315 Kinkead Hall
Lexington, KY 40506-0057
859 257-9428
fax 859 257-8995
www.research.uky.edu/ori/

Initial Review

Approval Ends
November 16, 2012

IRB Number
11-0907-P4S

TO:	Michael Abbot Maginnis 210E Center for Robotics and Manufacturing Systems 0108 PI phone #: (859) 257-4943
FROM:	Chairperson/Vice Chairperson Non-medical Institutional Review Board (IRB)
SUBJECT:	Approval of Protocol Number 11-0907-P4S
DATE:	November 21, 2011

On November 18, 2011, the Non-medical Institutional Review Board approved your protocol entitled:

Factors Affecting Continuous Improvement: Learning at the Team Member/Work Interface

Approval is effective from November 18, 2011 until November 16, 2012 and extends to any consent/assent form, cover letter, and/or phone script. If applicable, attached is the IRB approved consent/assent document(s) to be used when enrolling subjects. **[Note, subjects can only be enrolled using consent/assent forms which have a valid "IRB Approval" stamp unless special waiver has been obtained from the IRB.]** Prior to the end of this period, you will be sent a Continuation Review Report Form which must be completed and returned to the Office of Research Integrity so that the protocol can be reviewed and approved for the next period.

In implementing the research activities, you are responsible for complying with IRB decisions, conditions and requirements. The research procedures should be implemented as approved in the IRB protocol. It is the principal investigators responsibility to ensure any changes planned for the research are submitted for review and approval by the IRB prior to implementation. Protocol changes made without prior IRB approval to eliminate apparent hazards to the subject(s) should be reported in writing immediately to the IRB. Furthermore, discontinuing a study or completion of a study is considered a change in the protocol's status and therefore the IRB should be promptly notified in writing.

For information describing investigator responsibilities after obtaining IRB approval, download and read the document "PI Guidance to Responsibilities, Qualifications, Records and Documentation of Human Subjects Research" from the Office of Research Integrity's Guidance and Policy Documents web page [http://www.research.uky.edu/ori/human/guidance.htm#PIresp]. Additional information regarding IRB review, federal regulations, and institutional policies may be found through ORI's web site [http://www.research.uky.edu/ori]. If you have questions, need additional information, or would like a paper copy of the above mentioned document, contact the Office of Research Integrity at (859) 257-9428.

N. Van Tubergen Ph.D./ah
Chairperson/Vice Chairperson

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Publications & Patents

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